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Cognitive Load Increases Risk Aversion*

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Abstract

We investigate how stable individuals' risk attitudes are with respect to changes in cognitive load. In a laboratory experiment using pairwise lottery choice and a within-subject design, we show that putting subjects under load via a concurrent working-memory task significantly increases their risk aversion. Subjects made significantly faster choices under load. Regardless of load, they responded faster when choosing the less risky option in safe–risky trials, but not in risky–risky trials. We discuss how these findings relate to both dual-system and unitary-system theories of decision making. We observe that predictions of both recent dual-system and drift–diffusion models of the decision-making process are confirmed by our data and argue for a convergence of these to-date separate strands of the literature.

Keywords: Risk aversion, cognitive load, working memory, dual-system approach, multiple-system approach, dual-self model, drift–diffusion model, response times

JEL codes: C91, D03, D81, D87

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1 Introduction

Risk aversion is one of the key concepts in economics. Without risk aversion, many economic phenomena—such as the existence of insurance, the risk premia that investors receive on stocks vis-à-vis bonds, or consumption smoothing over the business cycle—could not be explained. In this paper, we investigate how stable people's risk attitudes are with respect to a specific change in the decision-making environment. We show via a laboratory experiment that putting subjects under cognitive load during pairwise lottery choice significantly increases their risk aversion.

Empirical investigations suggest that risk attitudes are state-dependent (e.g., Cohn et al., 2015), and several theoretical models have been developed to capture such state dependence. The relevant states are often taken to be previous economic outcomes, for instance, when agents are assumed to exhibit habit formation (e.g., Campbell and Cochrane, 1999) or when preference parameters are assumed to depend on realized gains and losses (e.g., Barberis et al., 2001). It is possible, however, that risk attitudes are not only influenced by past outcomes but also by concurrent factors in the economic environment. A potential concurrent factor is the extent to which people can deliberate on the decisions that they make. As an example, think of investors who may have to process a lot of information and make several decisions simultaneously in times of volatile markets, while they can deliberate more thoroughly in calmer periods.

We mimicked such a situation in our experiment by varying the working-memory load of subjects while they made decisions under risk. We used a within-subject design and let each of the 41 participants complete 2×60 pairwise lottery choices—some safe–risky, most risk–risky, all with strictly positive payoffs. During half of the trials, subjects performed a cognitively demanding distractor task concurrent to the lottery choice.

Our main result is that cognitive load increases risk aversion: Subjects chose the riskier, but on average more rewarding, lottery significantly less often when cognitive load was increased. To complement this non-parametric measure, we estimated the cognitive-load–induced change in subjects' risk aversion via several structural regressions. We find that subjects' average degree of risk aversion was significantly higher under load. For the lotteries used in our study, the risk premia implied by the estimated preference parameters, according to our baseline regression, were 6.9% in the "no load" condition and 7.7% in the "load" condition, an increase of 12.3%.

We also find that lottery choices were made significantly faster in the "load" than in the "no load" condition. In both conditions, subjects responded exceptionally fast when they chose the safe alternative in safe–risky trials. We consider response times an important measure in this type of study, since formal models of decision making often imply particular response time patterns. Thus, observed response times favor certain interpretations of subjects' behavior and oppose others. We address this when presenting (Section 4 and discussing (Section 5) our results.

So far, only two studies have investigated a potential link between cognitive load and risk aversion. The evidence is inconclusive. Both studies used a number memorization task to put subjects under cognitive load. Benjamin et al. (2013) let subjects choose repeatedly between a safe and a risky payoff or between two risky payoffs. Benjamin et al. find that cognitive load increases small-stakes risk aversion; however, only in "the case of comparisons of risky gambles, the effect is statistically significant" (p. 1249). This ambiguous finding may be the consequence of low statistical power, resulting from a between-subject design with only few observations per condition. Deck and Jahedi (2015) used a larger sample and a within-subject design. They combined a number memorization task with repeated pairwise choice between sure payoffs and lotteries. In contrast to Benjamin et al., Deck and Jahedi find a significant effect of cognitive load for safe–risky choices: an increase in the frequency with which subjects chose the safe option under load.

Deck and Jahedi (2015) interpret their finding as an increase in risk aversion. However, the choice frequencies of the two options approach 50% under load in their experiment, so that the effect that they observe may stem from a tendency toward random choice under load. It is exactly this issue that was raised by Franco-Watkins et al. (2006) and Franco-Watkins et al. (2010) regarding much earlier cognitive-load studies in the domain of intertemporal choice. This issue is absent in our study: The choice frequencies under load move away from 50% instead of approaching random choice. Moreover, via our structural regressions, we can estimate to which degree subjects made inconsistent choices. We do not find any evidence for a cognitive-load–induced tendency toward random choice. Apart from this, the results that we present in Section 4.2.2 indicate that safe–risky choices are qualitatively different from risky–risky choices (see also Dickhaut et al., 2003) so that analyzing both types of choices is important.

An approach that can explain our findings and that has been highly influential in psychology and cognitive neuroscience is the dual-system approach, in particular the "risk as feelings" hypothesis (Loewenstein et al., 2001). This hypothesis postulates that relatively slow cognitive and faster emotional processes, executed by different systems in the human brain, interact in decision making under risk. Existing experimental evidence suggests that the emotional system steers decisions in the direction of risk avoidance and the cognitive system in the direction of risk neutrality—see, e.g., Shiv et al. (2005) and Hsu et al. (2005) for studies with patients who suffered from specific brain damage; Hsee and Rottenstreich (2004) for a study that used emotional priming; and Rubinstein (2007, 2013) for response time studies. Since cognitive processes are working-memory–dependent (Evans, 2008, pp. 257/259), whereas emotional ones are not, the dual-system approach explains why lowering the impact of the cognitive system by taxing working memory leads to increased risk aversion.

A closely related approach has recently found its way into the economics literature in the form of "dual-self" models. Using a dual-self framework, Fudenberg and Levine (2006, 2011) formally derive the prediction that cognitive load increases risk aversion. Moreover, they show that their model predicts risk aversion to be particularly pronounced for choices between a safe and a risky alternative. We find evidence for both predictions.

While our findings are compatible with the dual-system/dual-self approach to decision making under risk, we also discuss how our findings relate to a different class of models, so-called "drift–diffusion" or "sequential sampling" models (e.g., Busemeyer and Townsend, 1993). These are highly influential in cognitive psychology and cognitive neuroscience and have recently received a lot of attention in the field of neuroeconomics (see, e.g., Basten et al., 2010; Fehr and Rangel, 2011; Clithero and Rangel, 2013). In a broader context, our findings suggest that people's preferences interact with the complexity of the environment in which they make a decision. This has potential implications for various fields of economics; for instance, investors' risk aversion may differ systematically between times of high and low market volatility.

In the remainder of this paper, we first briefly review the theoretical approaches and the empirical evidence that form the background of this study (Section 2). We then describe the design of our study (Section 3), followed by the statistical analysis and the results concerning choices and response times (Section 4). A discussion and interpretation of our findings conclude (Section 5).

2 Related Literature

The existing evidence on the relation between cognitive load and decision making under risk is inconclusive and relatively scarce.

Benjamin et al. (2013) provide evidence that risk attitudes can be influenced through the use of "higher-order cognitive processes" and through cognitive load: In one of their experimental conditions, subjects had to verbalize the reasons for their choices. This resulted in *fewer* risk-averse choices than in the control condition. In a different condition, Benjamin et al. subjected participants to a "'cognitive load' manipulation … designed to inhibit working memory": they asked participants to memorize a 7-digit number and incentivized correct recall. This *increased* participants' small-stakes risk aversion, both for choices between a sure payoff and a gamble as well as between two gambles. Only in the latter case, however, is the effect statistically significant (p. 1249).

Deck and Jahedi (2015) report the results of an experiment that also employed a number memorization task and combined it with incentivized choices between a sure payoff and a lottery. In contrast to Benjamin et al. (2013), Deck and Jahedi find a significant effect for safe–risky choices: an increase in the frequency with which subjects chose the safe option under cognitive load. Deck and Jahedi interpret this as an increase in risk aversion. However, as argued above, the manipulation effect that they observe may result from a tendency toward random choice under load, since the choice frequencies of the two options approach 50% in their load condition.

In summary, the existing evidence is only partially consistent across studies,[1] and its informativeness is limited by potential confounds.

A correlational between-subject finding analogous to increased risk aversion due to cognitive load would be that higher working-memory capacity is associated with lower

[1] It is actually even inconsistent within the study of Benjamin et al. (2013), who note in their online appendix (p. 5) that during a pilot study, none of the three different cognitive-load manipulations they tested "reliably influenced the preferences we measured."

risk aversion. According to Evans (2008, p. 262), it is “well established that individual differences in working memory capacity and general intelligence measures are very highly correlated.” Consequently, higher intelligence should go along with lower risk aversion. Indeed, this is what Dohmen et al. (2010) find in a representative sample of German adults. Their results are confirmed for different subject pools by Burks et al. (2009) and Benjamin et al. (2013).

The mentioned findings are often interpreted through a “dualistic” lens (e.g., Rubinstein, 2007: “instinctive” vs. “cognitive”; Benjamin et al., 2013, p. 1233). The dual-system approach views decision making as an interaction of dissociable systems in the human brain. It has a “long legacy of research within psychology, strongly supported by findings from neuroscience” (Sanfey et al., 2006, p. 111). The most neutral labels for the postulated systems are simply “System 1” and “System 2” (Stanovich and West, 2000). Distinguishing features ascribed to the two systems are speed, flexibility, and reliance on working memory. In contrast to the “high capacity” nature of System 1, System 2 seems to be more flexible, but also (i) limited by access to working memory and (ii) comparatively slow (Evans, 2008, p. 261/262). This implies that if risk attitudes are shaped by the interaction of both systems, (i) it should be possible to influence risk aversion by a task that taxes working memory, and (ii) response times can serve as an indicator of the dominating system.

Concerning response times, Rubinstein (2007) provides correlational evidence from an Internet-based experiment in which subjects were asked to choose between two hypothetical gambles. Rubinstein observes that choices of the less risky gambles were made substantially faster than choices of the riskier one. He interprets this as reflecting different modes of reasoning, “cognitive” and “instinctive.” Neither Benjamin et al. (2013) nor Deck and Jahedi (2015) analyze response times.

A special type of System-1 processes are emotions (see Evans, 2008, p. 256/258). Emotions can be defined as “low-level psychological processes engaged by events that elicit strong valenced and stereotyped behavioral responses.” They are “rapid” and “highly automatic” (Sanfey et al., 2006, p. 111). According to the “risk-as-feelings” hypothesis, decision making under risk is shaped by an interplay between emotional and cognitive responses that are “often conflicting” (Loewenstein et al., 2001, p. 270). Specifically, Hsee and Rottenstreich (2004) and Mukherjee (2010) posit that System-1 processing is strongly risk-averse, while System-2 processing is less so—such that weakening the influence of System 2 should increase risk aversion. The model by Fudenberg and Levine (2006, 2011) rests, in a broad sense, on the same idea.

Compatible with these views, Shiv et al. (2005) find that subjects with brain lesions “in specific components of a neural circuitry that has been shown to be critical for the processing of emotions” (p. 436) made significantly *fewer* risk-averse choices than control subjects. Similar evidence is reported by Hsu et al. (2005) who observe that patients with specific brain lesions were significantly less risk-averse than control subjects. Mohr et al. (2010) conducted a meta-analysis of related neuroimaging studies and find the evidence from this literature to be “compatible with … the risk-as-feelings hypothesis” (p. 6618). They ascribe the role of integrating the cognitive and the emotional information to the dorsolateral prefrontal cortex (dlPFC). The fact that brain stimulation studies have shown that stimulating the dlPFC affects individuals' risk attitudes (e.g., Fecteau et al., 2007) completes the picture.

Of course, the dual-system approach is not uncontested. Keren and Schul (2009, p. 534) criticize many descriptions of the presumed interplay of the two systems as being too vague, which makes it difficult to pitch dual-system against unitary-system models. Consequently, we also consider a unitary-system explanation of our findings: so-called drift–diffusion models (e.g., Busemeyer and Townsend, 1993) which have found a lot of empirical support in the field of neuroeconomics (see, e.g., the review by Fehr and Rangel, 2011). For details, see Section 5.

3 Design of the Experiment

3.1 General Information

The experiment was performed in November/December 2010 at Freie Universität Berlin. We tested $N = 41$ subjects (21 female; age: range, 19 to 47 yrs.; mean ± std. dev., 25.9 ± 5.95 yrs.). Subjects were recruited mainly among the students of the Berlin universities and via mailing lists to which previous and prospective subjects had registered. No inclusion or exclusion criteria applied. The majority of subjects (30 of 41) were students from various disciplines; the occupational backgrounds of the remaining subjects ranged from electricians to university employees to physicians.

We used a within-subject design, because we were rather interested in how variable people's preferences are over multiple decisions of the same kind in different situations, than how much the attitudes of different people in different situations vary when they make a single choice or only few choices. We consider a within-subject design externally more valid than a between-subject design, because humans make decisions over relatively small stakes, like the payoffs used in our experiment, repeatedly; in contrast, one-time decisions are likely to involve large stakes. Moreover, a within-subject design makes isolating the effect of a manipulation easier than a between-subject design, because the effect is not conflated with between-subject variation.

For display of the stimuli as well as recording the responses and response times, the software "Presentation" (Neurobehavioral Systems, Inc.) was used.

3.2 Conditions and Trials Types

There were two conditions within-subject: *no cognitive load*, i.e., the cognitive-load task was absent, and *cognitive load*. In the "no load" condition, subjects' only task was to choose one out of two offered lotteries. In the "load" condition, subjects had to remember an arrangement of dots on top of making the lottery choice. Each condition comprised 60 trials. The trials were presented in pseudo-random order in blocks of 15 trials. All trials within a block belonged to the same condition, to minimize carry-over effects between the conditions. A "load" trial lasted 17.75 sec and a "no load" trial 12.25 sec (see Figure 1).

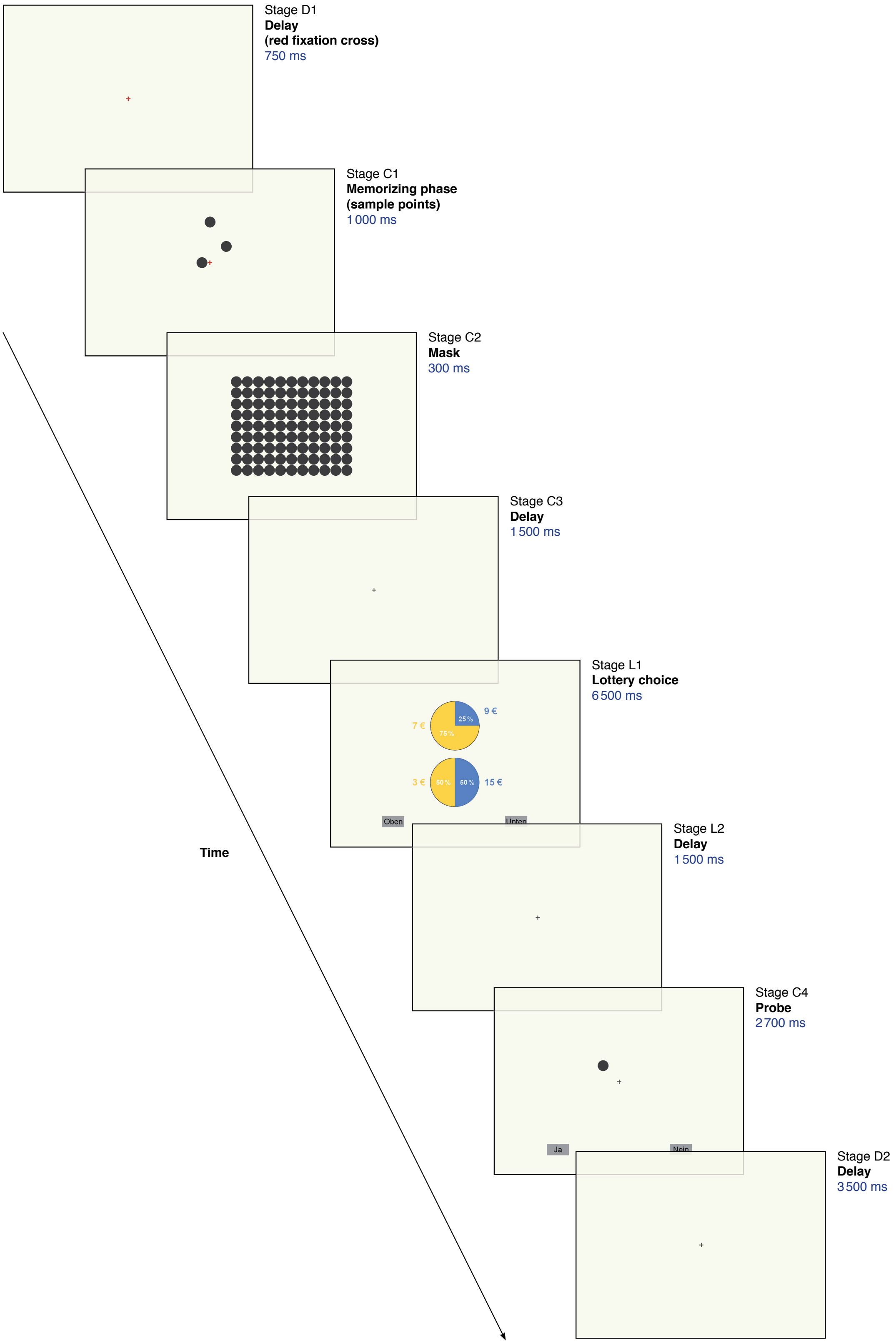

Figure 1. Trial setup in the “cognitive load” condition. In the “load” condition (60 trials), both lottery choice (Stages L1 and L2) and working-memory task (C1–C3 and C4) were present. In the “no load” condition (60 trials), Stages C1–C3 and C4 were omitted. In the 30 “working-memory task only” trials, Stages L1 and L2 were omitted.

The literature reviewed in Section 2 suggests that risk attitudes might covary with the individual difficulty of the working-memory task. Hence, it is useful to have an independent measure of task difficulty. To obtain this measure, we added 30 trials in which subjects performed only the working-memory task, without any lottery choice. Hence, there was a total of three trial types: the main types "load" and "no load," and the third type, "working-memory task only."

The experiment lasted around 45 min, including practice trials and breaks.

3.3 Remuneration

Subjects' remuneration included a show-up fee of €5. Remuneration for the lottery choice was based on one randomly selected trial (random-incentive mechanism). This was done to prevent subjects from hedging their decisions across trials, since the statistical analysis assumes choices to be independent across trials. The payoff was determined by randomly drawing a realization from the lottery which the subject had chosen in that trial. In addition, subjects received a reward of €5 upon answering correctly in the working-memory task. Again, one trial was selected randomly per subject to be the payoff-relevant trial. Thus, the reward for the working-memory task and the payoff from the lottery choice were independent of each other.

3.4 Pairwise Lottery Choice

We used a variant of the Random Lottery Pairs procedure (Hey and Orme, 1994): In each trial t, subjects were shown a lottery pair $\{\boldsymbol{A}_t, \boldsymbol{B}_t\}$ out of a set of 60 lottery pairs. The pairs were presented in pseudo-random order. The advantage of the Random Lottery Pairs procedure over other procedures, such as the Price List design (Holt and Laury, 2002), for our purposes is that the former makes it difficult to remember previous choices. Moreover, response times in pairwise lottery choice are easier to interpret than response times in Price List designs.

Each lottery $\boldsymbol{L}$ consisted of two possible, strictly positive payoffs $(x_1^{\boldsymbol{L}}, x_2^{\boldsymbol{L}})$ and was visualized by a pie chart of the associated probabilities $(p_1^{\boldsymbol{L}}, p_2^{\boldsymbol{L}}) = (p_1^{\boldsymbol{L}}, 1 - p_1^{\boldsymbol{L}})$ (see Figure 1), as is commonly done in experiments (see Harrison and Rutström, 2008). The payoffs ranged from €2 to €20, and the probabilities $p_1^{\boldsymbol{L}}$ were 10%, 25%, 50%, 75%, 90%, or 100%.

Subjects were asked to choose one of the two offered lotteries within a time frame of 6.5 sec. As soon as subjects had pressed a button to indicate their lottery choice, the selected lottery was marked by a red frame.[2] Subjects were allowed to change their selection within the mentioned time frame.

[2] To enable this visual feedback, a loop with an intended duration of 50 ms per iteration was executed during presentation of the lotteries. However, due to timing inaccuracies in the software, each iteration lasted 16 ms longer than programmed. This resulted in a somewhat longer time frame during which responses were possible than announced. Subjects do not seem to have noted the discrepancy in the course of the experiment—in fact, their lottery choices became significantly faster over time, see Section 4.2.1.

The lotteries differed from each other in their riskiness. According to the definition of "increased risk" by Rothschild and Stiglitz (1970), a lottery can be considered riskier than another lottery if it can be expressed as a mean-preserving spread (MPS) of the other lottery. Since risk averters dislike the wider spread, making them choose the riskier lottery requires adding some compensation for the wider spread to the riskier lottery—a "risk premium." We denote this risk premium by m. Within a lottery pair $\{\boldsymbol{A}_t, \boldsymbol{B}_t\}$, we thus call the lottery $\boldsymbol{A}_t$ the riskier lottery if it has a wider spread than $\boldsymbol{B}_t$, such that $\boldsymbol{A}_t = \mathrm{MPS}(\boldsymbol{B}_t) + m_t$, with m_t being a sure payoff. This criterion applies to 42 of the 60 lottery pairs we used.[3]

The 60 lottery pairs presented to subjects were designed such that for degrees of risk aversion in the range found in previous studies (see Harrison and Rutström, 2008), subjects would sometimes choose the riskier and sometimes the less risky lottery. To assess subjects' rationality and alertness, eight lottery pairs were generated such that one lottery first-order stochastically dominated the other one ("catch trials"), and in four lottery pairs, one lottery would be preferred for any degree of risk aversion. The complete set of lottery pairs is listed in Table A.1.

The location of the lotteries' visualization on screen was counterbalanced within-subject: In some trials, the riskier lottery was presented in the upper part of the screen, and in some in the lower part. Moreover, we counterbalanced the position of the larger payoff on screen between subjects: For half of the subjects, the larger payoff was illustrated by the left side of the pie chart, and for the other half, by the right side.

3.5 Cognitive-Load Manipulation

As the cognitive-load manipulation, we chose an incentivized version of a spatial-working-memory–delayed-matching task that had been used previously (e.g., in Nagel et al., 2009). Subjects were briefly (1 sec) shown an arrangement of points, called "sample points." Subjects knew that they would have to indicate after a short delay whether a single point presented to them, called "probe," matched any of the sample points (see Figure 1)—hence the name "delayed-matching task."

The arrangement of the sample points varied across trials. The locations of the different points were determined by placing them on virtual radii around the fixation cross shown at the center of the screen (as in Nagel et al., 2009).

During the delay between the memorizing and the probe phase—i.e., while keeping the arrangement of points in mind—subjects made a lottery choice.

In the probe phase, subjects indicated via a button press whether the probe corresponded to any of the sample points or not. To avoid ambiguity in the categorization, the probe was placed such that it occupied either the exact same spot as a sample point or

[3] An alternative—which is theoretically less well founded—is to consider a lottery's variance as an indicator of its riskiness. If a mean–variance trade-off is present in a lottery pair, one calls the lottery that features the higher variance, but also the higher average payoff, "riskier." This criterion applies to 51 of our 60 lottery pairs. A wider spread implies larger variance, but not vice versa. Hence, the two measures coincide in many but not all of our trials.

a non-overlapping position (as in Nagel et al., 2009). Except in the initial practice trials, subjects did not receive feedback during the experiment.

We chose this task instead of a number memorization task as it was used, e.g., by Benjamin et al. (2013), since we desired a large number of observations per subject. Our load task makes this possible by keeping both the memorizing and the probe phase, which requires a single button press for "yes" / "no," short.

3.6 Practice Trials

Subjects could familiarize themselves with the experimental design over the course of 30 practice trials. The first 10 practice trials consisted of the working-memory task alone, and the next 10 of the lottery choice task alone. Both tasks were combined in the last 10 practice trials.

3.7 Measures of Individual Differences

After the experiment, subjects performed the Cognitive Reflection Test (Frederick, 2005) and filled in a questionnaire on sociodemographic data.

4 Results

We first check whether the tasks in the experiment were adequately chosen. In only 6 out of 4,920 (41×120) lottery choices (0.12%) did subjects not respond on time. There was not a single missed answer in the working-memory task ($41 \times 90 = 3690$ trials). The average hit rate in the working-memory task was 91.30% in the "working-memory task only" trials, and it decreased to 78.94% when the lottery choice task was present. Such a decrease could be observed on the individual level for all but two subjects. Hence, subjects do not seem to have focused exclusively on the working-memory task but also paid attention to the lottery choice task.

At the same time, the hit rates in the working-memory task were above chance level (50%) for all subjects even in the presence of the lottery choice. This is significant for all subjects but one on the 5% level and for all subjects on the 10% level. Hence, the incentive to perform well in the working-memory task seems to have been adequate: Subjects did not focus exclusively on the lottery choice.

Taken together with the response times (Section 4.2), these observations indicate that the tasks, including the permitted response times and the incentives for both tasks, were adequately chosen.

4.1 How Often Did Subjects Choose the Riskier Lottery?

4.1.1 All Trials (Risky–Risky and Safe–Risky) Pooled

Since each lottery pair was offered to each subject twice—once in the "no load" and once in the "load" condition—we are able to test whether the experimental manipulation led to

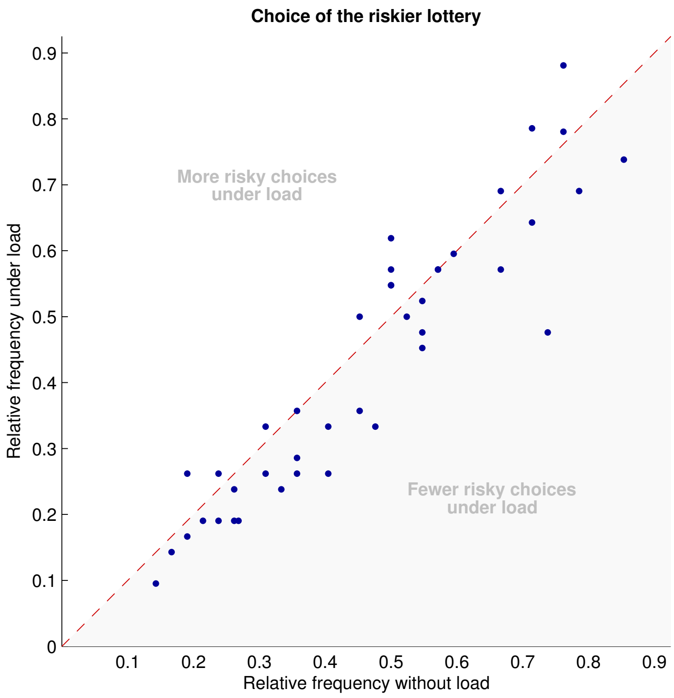

Figure 2. Choice of the riskier lottery under working-memory load and in the absence of working-memory load. Each point indicates one subject. The relative frequency for each subject is based on 42 pairwise choices for each condition between a riskier and a less risky lottery (41 choices in three cases, because three subjects failed to respond within the time limit in one trial each, two in the "no load" and one in the "load" condition).

choice reversals. As stated in Section 3, we expected choice reversals to be predominantly of the kind that if the riskier lottery is chosen from a given pair in the absence of cognitive load, the less risky option is chosen under load.

Consistent with this hypothesis, the frequency with which the riskier lottery was chosen is lower in the "cognitive load" condition: 53.8% vs. 56.9%. The fact that the majority of points lies below the 45° line in Figure 2 reveals that the aggregate reduction in the frequency of riskier choices is not the result of a small number of subjects exhibiting a rather strong effect, but of a robust small effect across subjects. A Wilcoxon signed-rank test of the differences in subjects' choice frequencies between the two conditions yields that the observed effect is statistically significant ($p = 0.012$; $N = 41$).[4, 5]

Result 1. *Subjects choose the less risky lottery significantly more often in the presence than in the absence of cognitive load, indicating higher risk aversion under cognitive load.*

[4] $p = 0.026$ if the variance criterion is used. Given that the MPS and the variance criterion for calling a lottery "riskier" often coincide, we obtain qualitatively identical results in most cases.

[5] A complementary approach is to perform a probit regression of the choices on a constant and on a dummy for the "load" condition. Using a two-stage regression—to be able to include random individual effects in both the constant and the "load" dummy—we find a significant effect of cognitive load ($p = 0.0161$). The coefficient of correlation between the choice frequencies depicted in Figure 2 and the estimated individual random effects amounts to 0.999 in the "no load" and to 0.962 in the "load" condition, indicating that the random-effects specification performed well.

Importantly, we find evidence that the observed less frequent choice of the riskier lottery under cognitive load does not stem from a tendency towards random choice. One could mistake a change of the choice frequencies due to random choice for a systematic change if the relative choice frequencies under load approached 50%.[6] In our data, the opposite holds: The less risky lottery is chosen in the majority of cases (53.8%) in the absence of load, and it is chosen even more frequently (56.9%) under load. Thus, the observed influence of cognitive load on subjects' choices is probably not due to a load-induced tendency towards random choice. We will return to the topic of noise in subjects' choices in the context of our structural regressions.

4.1.2 Risky–Risky vs. Safe–Risky Trials

Fudenberg and Levine (2011, p. 66) mention as a testable prediction of their model that completely safe alternatives are particularly "tempting," such that "introducing cognitive load when the alternative is safe induces many subjects to switch to the safe alternative, while there is no such reversal when the 'safe' alternative is" less risky but nevertheless probabilistic. At the same time, the model by Fudenberg and Levine (2011) predicts a particular attractiveness of safe payoffs also in the absence of cognitive load (see p. 35). The described phenomenon of increased risk aversion in the presence of a safe alternative is known as the "certainty effect" (Kahneman and Tversky, 1979; see Dickhaut et al., 2003, for relevant neuroimaging evidence).[7]

The behavior of subjects in our experiment is in line with the predictions of the Fudenberg–Levine model to the extent that in the absence of load, subjects chose the lottery in the safe–risky trials in only 27.87% of cases, vis-à-vis 49.9% in the risky–risky trials. This value goes down to 20.56% for the safe–risky trials and to 47.6% for the risky–risky trials in the presence of cognitive load. Out of the 41 subjects, 10 subjects exclusively chose the safe payoff in the absence of load—under load, 18 subject exhibited this behavior, among them all ten subjects who always chose the safe alternative even in the absence of load.

When analyzing the risky–risky and the safe–risky trials separately, the load-induced effect turns out to be marginally significant according to a Wilcoxon signed-rank test for the risky–risky trials ($p = 0.098$), while it is is highly significant for the safe–risky trials ($p = 0.004$). We test whether the potential interaction of the effect of cognitive load with the presence of a sure payoff is statistically significant. A Wilcoxon signed-rank test reveals the interaction to be marginally significant ($p = 0.079$).[8] Hence, we find some support for the prediction of the Fudenberg–Levine (2011) model that cognitive load has a particularly strong influence in safe–risky choices, but the evidence is not particularly strong.

[6] The debate between Franco-Watkins et al. (2010) and Hinson et al. (2003) about whether cognitive load aggravates temporal discounting concerns a possible misinterpretation of this kind.

[7] "[P]eople overweight outcomes that are considered certain, relative to outcomes which are merely probable—a phenomenon which we label the *certainty effect*" (Kahneman and Tversky, 1979, p. 265).

[8] So does modeling the interaction in the probit regression ($p = 0.073$).

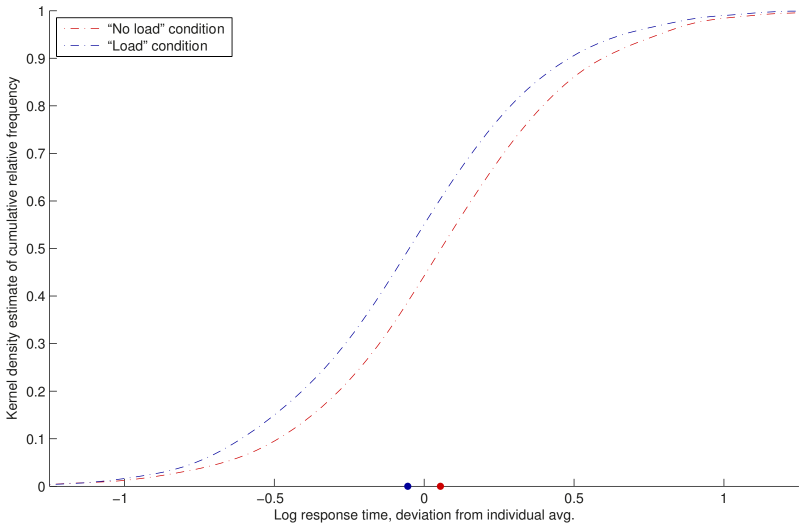

Figure 3. Cumulative distributions of the log response times for the lottery choice in the presence and absence of the working-memory task.

Result 2. *Subjects show a pronounced tendency to avoid the riskier option in safe–risky trials, in both the "load" and the "no load" condition. This is in line with the "certainty effect" and the model by Fudenberg and Levine (2011). The marked disinclination to choose the risky option in safe–risky trials is even strengthened by concurrent cognitive load, as predicted by the Fudenberg–Levine model; this effect is, however, only marginally significant* ($p < 0.10$).

The reason behind the interaction not being more pronounced might be a ceiling effect: Given that the disinclination to choose the risky alternative in the safe–risky trials is already quite extreme in the absence of cognitive load, there was not much room for the working-memory task to increase risk aversion even further.

4.2 Response Times

To gain a deeper understanding of the causal influence of cognitive load on decision making, we now take a look at subjects' response times. Analyzing response times serves two functions: First, they provide data that can be used to test predictions of models of decision making. Second, they indicate, according to several prominent theoretical accounts, how difficult a decision was (see Clithero and Rangel, 2013, and the references therein). Hence, response times should be included as a regressor when performing structural regressions to explain behavior, because they may be related to the noise in people's choices, i.e., to the likelihood that people make errors.

4.2.1 Influence of Cognitive Load on Response Times in the Lottery Choice Task

It turns our that the vast majority of subjects responded *more quickly* in the lottery choice task when performing the working-memory task simultaneously. This is evident from Figure 3 which depicts pure within-subject variation in response times: It plots the cumulative distributions—estimated via kernel density estimation—of the deviation of subjects' log response times from their respective individual averages.[9] It turns out that the curve for the "load" condition lies strictly to the left of the curve for the "no load" condition, indicating that the entire distribution of the response times is shifted towards lower values under load.

The average response time across all subjects in the "no load" condition is 3,835 ms, while it is 3,449 ms in the "load" condition, a reduction by 10.1%. A regression of the log response times on individual fixed effects—to account for the substantial heterogeneity in subjects' average response times—and on a condition dummy reveals that this effect is significant ($p < 0.001$).

Result 3. *Subjects' lottery choices are 10% faster* ($p < 0.001$) *in the presence of cognitive load than in its absence.*

One might have expected the reverse effect: that the multi-tasking demands of the "cognitive load" condition led to an increase in the time needed to make a decision in the lottery choice task. Our finding is in line, though, with previous evidence: a decrease was also observed by Whitney et al. (2008, p. 1182). They conjecture "that participants were speeding up their decision-making processes … in order to maintain high accuracy on the WM load task." Notably, in their design, just like in ours, faster choice between the lotteries did *not* lead to an earlier display of the probe phase of the working-memory task.

The question whether faster lottery choices improve performance in the working-memory task is important because one might suspect that the channel through which concurrent cognitive load influences risk attitudes is by generating time pressure during the lottery choice—or at least a feeling thereof. Unfortunately, this hypothesis is difficult to test, since the counterfactual is missing: how well would subjects have performed in the working-memory task, had they taken more time in the lottery choice?[10] To be on the

[9] The distribution of the response times in the lottery choice task in our experiment is—as usual—strongly right-skewed. Therefore, we apply the log transformation that is typically used in the analysis of response times when response times are the dependent variable (but not when it is an explanatory variable). Ulrich and Miller (1994, p. 40) write that the lognormal distribution and other skewed distributions "all have been found to give particularly good fits to empirical RT distributions." Hence, by using log response times as the dependent variable, we effectively analyze changes in the mean of the Gaussian component of the response time distribution. The transformation has the consequence that the coefficient associated with a particular explanatory variable indicates a percentage change in the average response time for a one-unit change in that explanatory variable. The transformation also has the effect that the assumptions of the statistical tests concerning the distribution of the residuals are not violated (as we checked by examining normal Q–Q plots of the residuals of our regressions with the log-tranformed response times as the dependent variable).

[10] To proxy for the counterfactual "what if subjects had taken more time in the lottery choice," we conducted a split-sample analysis: did subjects perform worse in the working-memory task in those trials where their response time in the lottery choice was above the mean response time in the lottery choice without load? This was not the case: the difference was a mere 0.3% improvement in the hit rate, and it was not significant (Wilcoxon signed-rank test, $p = 0.7167$). Between subjects, we find that the average hit rate in the working-memory task is indeed the higher, the lower the average log response time for the lottery choice (coefficient of

safe side, we include response times as a potential determinant of expressed risk attitudes in our structural regressions below (Section 4.3.4).

The combination of stronger risk aversion and speedier decisions under cognitive load is consistent with the observation by Rubinstein (2007, 2013) that his subjects made choices of the less risky of two options more quickly than choices of the riskier option. Rubinstein interprets the response times that he observed as evidence for the use of either a "cognitive" or an "instinctive" decision-making process. However, Rubinstein's studies are purely correlational—they were based on a between-subject design without any exogenous manipulation of the decision-making environment.

4.2.2 Influence of the Presence of a Sure Payoff on Response Times

Since we collected multiple choices per condition per subject, we can improve on Rubinstein's (2007; 2013) analyses by within-subject estimation of differences in response times that arise from choice of the riskier or the less risky lottery. Figure 4 plots the cumulative frequencies of the log response times in analogue to Rubinstein's analyses. That is, it depicts four curves: two for safe–risky and two for risky–risky trials, depending on the choice of the less risky (safe) or riskier lottery. For simplicity, we abstract from the effect of cognitive load in this plot, since it turns out that concurrent load shifts all four curves to the left by approximately the same amount[11] (see Figure A.1 for comparison).

The crucial finding illustrated by Figure 4 is that one type of decision stands out: Selecting the safe option in the safe–risky trials takes subjects much less time than all other types of decisions. When regressing the log response times on individual fixed effects and dummy regressors for choice of the less risky option in the safe–risky and risky–risky trials, respectively, we find that choices of the safe option were, on average, made 44% faster than choices of the risky option in the safe–risky trials (47% in the absence of load and 40% under load; all p-values < 0.001).

Corroborating this evidence, when we analyze those trials in which one of the payoffs was associated with a probability of 90%—i.e., the less risky lottery was close to safe—we find the same pattern: choices of the less risky alternative were made on average 12% faster than choices of the riskier lottery ($p < 0.001$).

One can interpret this observation as further evidence that a safe option is particularly attractive to subjects—as the "certainty" effect posits. Corroborating such an interpreta-

correlation, $r = -0.261$, $p = 0.099$). This measure, however, may be confounded by ability. Indeed, Figure A.2 illustrates that the respective within-subject effect is less pronounced than this between-subject effect. In the associated logit regression that models success in the working-memory as a function of the response time in the lottery choice, the coefficient has the anticipated sign, but the marginal effect is not significant and negligible: a mere 1.3% improvement of the hit rate in the working-memory task if subjects responded an entire second faster in the lottery choice.

[11] When we regress the log response times on individual fixed effects and appropriate dummy regressors for choice of the riskier/less risky option in the safe–risky or risky–risky trials, respectively, as well as on a dummy for the presence of concurrent cognitive load plus appropriate interaction terms, we find all interaction effects not to be significant (all p-values > 0.206).

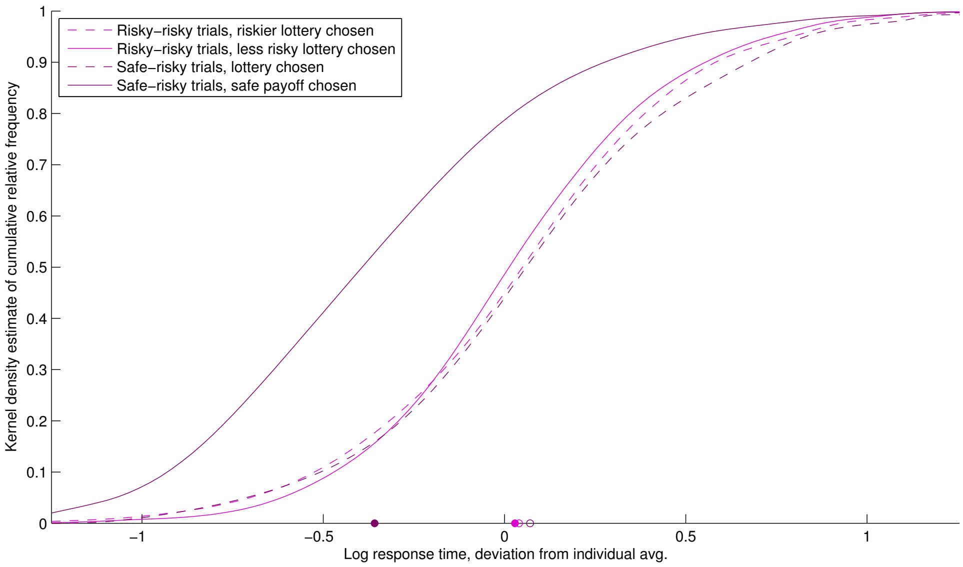

Figure 4. Distributions of the log response times in the lottery choice task (within-subject variation, i.e., deviation from the individual average log response time): presence / absence of sure payoff × risky / less risky alternative chosen.

tion, we find between-subjects that the more often subjects chose the safe option, the more quickly they did so ($r = 0.571$, $p < 0.001$).

Result 4. *Subjects respond particularly fast when they choose the safe option in safe–risky trials, both in the absence and in the presence of load.*

Mean response times for the three remaining types of choices (risky lottery in safe–risky trials, less risky lottery in risky–risky trials, and riskier lottery in risky–risky trials) do not differ significantly from each other (all p-values > 0.135).

According to the model by Fudenberg and Levine (2011), lottery choice is determined by the interaction of a myopic, risk-averse short-run self and a patient long-run self. The long-run self is able to "control" the short-run self at a cost. The authors draw heavily on constructs from the psychological multiple-process literature such as "self-control" / "impulse control" and use these terms repeatedly. Even though the Fudenberg–Levine model is not a process model and therefore makes no predictions on response times, one can still consider our response time findings as evidence for their model: an interaction of two motivations as formalized in their model could explain why risk-avoiding choices are made very quickly, while choosing the risky option takes substantially longer—because deliberative thinking needed to override the impulse of choosing the safe alternative is effortful, i.e., time-consuming.

To sum up, we find that it took subjects longer to decide in the "no load" than in the "load" condition. At the same time, we find that risk aversion expressed in subjects' lottery choices was increased under cognitive load. We also find that choices of the safe option in the safe–risky trials were made exceptionally quick—which one might interpret as support for the model proposed by Fudenberg and Levine (2011). A question that arises from our analysis is to which extent cognitive load affects risk attitudes directly and to which degree it does so indirectly, by putting subjects under—perceived—time pressure. This question, among others, is addressed in the following subsections.

4.3 Structural Regressions: Influence of Cognitive Load on Preference Parameters

Our previous analysis via checking for choice reversals uses a rather limited information set: it does not take into account how similar in terms of subjective valuation the lotteries were for which the reversals occurred. This drawback can be overcome by using structural regression models, which inherently rely on assuming a subjective valuation of the available alternatives. In this framework, checking for an effect of cognitive load on risk attitudes amounts to testing whether estimated preference parameters change between the two conditions.

The use of additional information compared with counting choice reversals comes at the cost of stronger assumptions. These are: (i) Subjects approximately maximize a latent value function, e.g., expected utility (EU) or rank-dependent utility (RDU). (ii) Their choices can be well explained by a particular functional form of the subjective valuation. (iii) Subjects bracket choices narrowly, i.e., only the payoffs from the experiment enter their valuation, and they consider each trial in isolation. The latter is rational in our experiment, since we used a random-incentive mechanism. For empirical evidence on narrow bracketing, see Rabin and Weizsäcker (2009).

A benefit of these stronger assumptions is that the modeling of noise (errors) in subjects' decisions becomes possible—of course, conditionally on the above assumptions. A second benefit is that one can compare our estimates of subjects' preference parameters to those from related studies—whereas the number of choice reversals is hard to compare across studies, since all studies use different sets of lottery pairs.

4.3.1 Estimation

We use several structural regressions in the form of a latent-variable logit model to estimate the effect of the cognitive-load manipulation on preference parameters. Let the vector $\boldsymbol{\theta}$ collect all preference parameters to be estimated. A lottery $\boldsymbol{L}$ is a list of payoffs $x_i^{\boldsymbol{L}}$ [in €] and associated probabilities $p_i^{\boldsymbol{L}}$, $i \in \{1,2\}$: $\boldsymbol{L} \equiv (x_1^{\boldsymbol{L}}, p_1^{\boldsymbol{L}}; x_2^{\boldsymbol{L}}, p_2^{\boldsymbol{L}}) = (x_1^{\boldsymbol{L}}, p_1^{\boldsymbol{L}}; x_2^{\boldsymbol{L}}, 1 - p_1^{\boldsymbol{L}})$. For each lottery pair $\{\boldsymbol{A}, \boldsymbol{B}\}$, given the preference parameters $\boldsymbol{\theta}$, a subjective value difference is determined—the latent variable, which we call "V-difference" (borrowing from Wilcox, 2011):

$$\Delta V(\boldsymbol{A}, \boldsymbol{B}; \boldsymbol{\theta}) \ = \ V(\boldsymbol{A}; \boldsymbol{\theta}) - V(\boldsymbol{B}; \boldsymbol{\theta}).$$

A decision maker whose preferences can be represented by the subjective value function $V(\boldsymbol{L}; \boldsymbol{\theta})$ chooses $\boldsymbol{A}$ from $\{\boldsymbol{A}, \boldsymbol{B}\}$ if $\Delta V(\boldsymbol{A}, \boldsymbol{B}; \boldsymbol{\theta}) > 0$ and $\boldsymbol{B}$ if $\Delta V(\boldsymbol{A}, \boldsymbol{B}; \boldsymbol{\theta}) < 0$. Of course, subjects generally do not make choices that are perfectly consistent with each other or with the assumed model. Binary-choice regressions account for this by mapping the

V-difference to choice probabilities via a strictly increasing, symmetric link function, $F\colon (-\infty,+\infty) \to (0,1)$. That is, $F[-v] = 1 - F[v]$, thus $F[0] = ½$, so that

$$\Pr[\boldsymbol{A} \,|\, \{\boldsymbol{A},\boldsymbol{B}\};\boldsymbol{\theta},\sigma] \;=\; F\left[\frac{\Delta V(\boldsymbol{A},\boldsymbol{B};\boldsymbol{\theta})}{\sigma}\right] \;=\; 1 - \Pr[\boldsymbol{B} \,|\, \{\boldsymbol{A},\boldsymbol{B}\};\boldsymbol{\theta},\sigma].$$

The parameter σ governs the dispersion (flatness) of the link function and is called the Fechner noise parameter (see Harrison and Rutström, 2008, p. 76). The larger σ (i.e., the more noise), the smaller the fraction gets, such that $F \to ½$ (random choice) for $\sigma \to \infty$. Conversely, $\sigma \to 0$ indicates complete absence of noise: subjects' choices are fully consistent with the assumed model. The link function F is the logistic function, $F[v] \equiv 1 / [1 + \mathrm{e}^{-v}]$, in the case of the logit specification.

Let $\boldsymbol{C}_t$ denote the lottery that was chosen in trial t, and let $\mathbf{1}$ be the indicator function: $\mathbf{1}_{\boldsymbol{A}_t}(\boldsymbol{C}_t) \equiv 1$ if $\boldsymbol{A}_t$ was chosen and 0 if $\boldsymbol{B}_t$ was chosen. (The few trials in which subjects failed to respond are omitted from our analysis.) Let $D_{\mathrm{CL},t}$ be a dummy regressor that equals 1 in trials t belonging to the "cognitive load" condition and 0 otherwise. Denote additional regressors by $\mathbf{z}_t = z_{t,1}, \ldots, z_{t,J}$, and let T be the total number of trials in the experiment.

Maximum likelihood estimation maximizes the log-likelihood

$$\begin{aligned}
&\ell(\boldsymbol{\theta},\boldsymbol{\delta}_{\boldsymbol{\theta}},\sigma,\delta_\sigma,\boldsymbol{\Gamma}_{\boldsymbol{\theta}},\boldsymbol{\gamma}_\sigma) \;\equiv \\
&\quad \sum_{t=1}^{T} \Bigg\{ \mathbf{1}_{\boldsymbol{A}_t}(\boldsymbol{C}_t) \quad \ln F\left[\frac{\Delta V(\boldsymbol{A}_t,\boldsymbol{B}_t;\boldsymbol{\theta} + \boldsymbol{\delta}_{\boldsymbol{\theta}}\, D_{\mathrm{CL},t} + \boldsymbol{\Gamma}_{\boldsymbol{\theta}}\, \mathbf{z}_t')}{\sigma + \delta_\sigma\, D_{\mathrm{CL},t} + \boldsymbol{\gamma}_\sigma\, \mathbf{z}_t'}\right] \;+ \\
&\qquad [1 - \mathbf{1}_{\boldsymbol{A}_t}(\boldsymbol{C}_t)]\, \ln\left\{1 - F\left[\frac{\Delta V(\boldsymbol{A}_t,\boldsymbol{B}_t;\boldsymbol{\theta} + \boldsymbol{\delta}_{\boldsymbol{\theta}}\, D_{\mathrm{CL},t} + \boldsymbol{\Gamma}_{\boldsymbol{\theta}}\, \mathbf{z}_t')}{\sigma + \delta_\sigma\, D_{\mathrm{CL},t} + \boldsymbol{\gamma}_\sigma\, \mathbf{z}_t'}\right]\right\}\Bigg\}. \qquad (1)
\end{aligned}$$

That is, the estimates are $(\hat{\boldsymbol{\theta}},\hat{\boldsymbol{\delta}}_{\boldsymbol{\theta}},\hat{\sigma},\hat{\delta}_\sigma,\hat{\boldsymbol{\Gamma}}_{\boldsymbol{\theta}},\hat{\boldsymbol{\gamma}}_\sigma) \equiv \arg\max \ell(\boldsymbol{\theta},\boldsymbol{\delta}_{\boldsymbol{\theta}},\sigma,\delta_\sigma,\boldsymbol{\Gamma}_{\boldsymbol{\theta}},\boldsymbol{\gamma}_\sigma)$. $\boldsymbol{\theta}$ denotes the baseline values of the preference parameters, i.e., in the absence of cognitive load. $\boldsymbol{\delta}_{\boldsymbol{\theta}}$ captures the changes in the preference parameters and δ_σ the change in the Fechner noise parameter that result from the presence of cognitive load.

The controls $\mathbf{z}_t$ may be specific for trial t (e.g., the difficulty of the load task in t) or subject-specific (say, gender or age; alternatively, individual fixed or random effects). The coefficient $\gamma_{\boldsymbol{\theta},i,j}$, i.e., the entry at position (i,j) in $\boldsymbol{\Gamma}_{\boldsymbol{\theta}}$, indicates by how much the preference parameter θ_i changes in response to a one-unit change of regressor $z_{t,j}$.

In this type of analysis, the subjective value $V(\boldsymbol{L};\boldsymbol{\theta})$ is frequently set equal to the expected utility of the respective lottery or—when taking probability weighting into account—to rank-dependent utility. However, Wilcox (2011) shows that this disconnects being "stochastically more risk-averse" from being "more risk-averse" in the theoretical sense (Pratt, 1964).[12] Wakker (2010, p. 85) as well as von Gaudecker et al. (2011, p. 676) solve

[12] As an illustration, consider choice between a lottery $\boldsymbol{A}$ and a sure payoff B, with $\mathrm{E}[\boldsymbol{A}] = B$, and assume power utility, $u(x;\rho) \equiv (x^{1-\rho} - 1) / (1-\rho)$. With $\Delta V = \Delta\mathrm{EU}$, it can happen that an increase in risk aversion, i.e., a more pronounced curvature of the utility function ($\rho \uparrow$), leads to $\Delta\mathrm{EU} \to 0$. Thus, the predicted probability that the sure payoff B is chosen from the pair $\{\boldsymbol{A},B\}$ would approach ½ for high ρ—which is nonsensical, since it should approach 1 when risk aversion rises.

the issue by using as the V-difference the difference between the lotteries' certainty equivalents. Formally,

$$\Delta V(\boldsymbol{A},\boldsymbol{B};\boldsymbol{\theta}) \;\equiv\; \Delta\mathrm{CE}(\boldsymbol{A},\boldsymbol{B};\boldsymbol{\theta}) = \mathrm{CE}(\boldsymbol{A};\boldsymbol{\theta}) - \mathrm{CE}(\boldsymbol{B};\boldsymbol{\theta}), \tag{2}$$

where $\mathrm{CE}(\boldsymbol{L};\boldsymbol{\theta}) \equiv u^{-1}\left[U(\boldsymbol{L};\boldsymbol{\theta});\boldsymbol{\theta}\right]$ is the certainty equivalent of lottery $\boldsymbol{L}$. $U(\boldsymbol{L};\boldsymbol{\theta})$ denotes lottery $\boldsymbol{L}$'s utility. We assume that it is given by expected utility,

$$U(\boldsymbol{L};\boldsymbol{\theta}) \;\equiv\; \mathrm{EU}(\boldsymbol{L};\boldsymbol{\theta}) = p_1^{\boldsymbol{L}}\, u(x_1^{\boldsymbol{L}};\boldsymbol{\theta}) + (1-p_1^{\boldsymbol{L}})\, u(x_2^{\boldsymbol{L}};\boldsymbol{\theta}).$$

We assume that subjects displayed either constant relative risk aversion (CRRA, "power utility") or constant absolute risk aversion (CARA, "exponential utility") with respect to the experimental payoffs:

$$u^{\mathrm{pow}}(x;\rho) \equiv \begin{cases} \dfrac{x^{1-\rho}-1}{1-\rho} & \text{if } \rho \neq 1 \\ \ln x & \text{if } \rho = 1 \end{cases} \quad \text{and} \quad u^{\mathrm{exp}}(x;\mu) \equiv \begin{cases} \dfrac{1-\mathrm{e}^{-\mu x}}{\mu} & \text{if } \mu \neq 0 \\ x & \text{if } \mu = 0 \end{cases}.$$

In both cases, an increase in the parameter (ρ or μ, respectively) indicates higher risk aversion. Both specifications are frequently used in the analysis of experimental data (see, e.g., Harrison and Rutström, 2008, and Andreoni and Sprenger, 2012).

4.3.2 Baseline Structural Regressions

In the baseline regressions, the influence of cognitive load is the only covariate. Since people differ in their attitudes toward risk—as is evident from the dispersion of the choice frequencies depicted in Figure 2—it is necessary to allow for individual heterogeneity in the statistical analysis, which we do by including individual random effects in ρ and μ, respectively.

The results of our baseline regressions are provided in Table 1. According to both the baseline "CRRA" and the baseline "CARA" regression, the cognitive-load manipulation significantly increased subjects' degree of risk aversion: The estimated coefficients $\hat{\delta}_\rho$ and $\hat{\delta}_\mu$, respectively, are significantly positive.[13]

If we count all choices $\boldsymbol{C}_t$ for which $\Pr[\boldsymbol{C}_t \,|\, \{\boldsymbol{A}_t, \boldsymbol{B}_t\}; \hat{\boldsymbol{\theta}}, \hat{\sigma}] > 0.5$ according to the model, as correctly predicted, then the fraction of correctly predicted choices is up to 73.03% (Regression CARA in the "load" condition). This is a satisfactory value given the results of studies that investigated the consistency of subjects' choices in pairwise lottery choice tasks (see Rieskamp et al., 2006, p. 634).

[13] We checked that the results are robust w.r.t. different starting values. In particular, we tried negative starting values for δ_ρ and δ_μ, respectively; the algorithm still converges to the reported significantly positive values. A different robustness check was using probit instead of logit estimation. Both yielded virtually identical fits, without a consistent ordering: For some specifications, the probit model performed slightly better, and for others, the logit model. Our result that cognitive load increases risk aversion does not depend on the choice of the link function.

Table 1. Results of the structural regressions.

Coefficient	CRRA Estimate	CRRA p-value	CARA Estimate	CARA p-value
$\hat{\rho}$ or $\hat{\mu}$	0.6958	0.000	0.0968	0.000
$\hat{\delta}_\rho$ or $\hat{\delta}_\mu$	0.0949	0.002	0.0129	0.002
$\hat{\sigma}$	0.7847	0.000	0.7691	0.000
$\hat{\delta}_\sigma$	0.0087	0.893	−0.0189	0.755
BIC	5,477.1		5,420.1	

Notes: Estimates based on $T = 4{,}914$ choices by $N = 41$ subjects. Logit model, non-linear maximum likelihood estimation, all subjects pooled, allowing for between-subject heterogeneity in ρ or μ via individual random effects The estimation was performed with MATLAB R2013a, using the `nlmefit` function. "CRRA": constant relative risk aversion (power utility). "CARA": constant absolute risk aversion (exponential utility). "BIC": Bayesian Information Criterion, calculated as $-2\,\ell(\hat{\rho},\hat{\delta}_\rho,\hat{\sigma},\hat{\delta}_\sigma) + k \ln N$, where N is the number of subjects, and k is the number of fitting parameters; here, $k = 6$.

Result 5. *Also according to our structural regressions, cognitive load significantly increases risk aversion.*

The Bayesian Information Criterion (BIC) of the exponential utility ("CARA") specification turns out to be lower than that of the power utility ("CRRA") specification.[14] That is, judged by the BIC, the CARA specification fits the data best, which is why we make it the basis of our subsequent analyses.[15]

To assess the magnitude of the observed effects, it is useful to translate the changes in preference parameters into changes in monetary units. Averaged over all subjects (taking the individual random effects into account) and over all lotteries used in our study, the estimated preference parameters according to the CARA specification imply risk premia of €0.65 (or 6.9%) in the "no load" condition and €0.73 (or 7.7%) in the "load" condition, an increase of 12.3%. We consider this a sizable effect, given that people make decisions of this small-stakes kind multiple times every day.

[14] For completeness, we checked that allowing for an influence of cognitive load on preferences significantly improves the model's fit. This is the case: A model (with CARA utility function) in which δ_μ and δ_σ are restricted to zero has a significantly worse fit (likelihood ratio test, $p = 0.021$).

[15] To check whether allowing for between-subject variation also in the Fechner noise parameter and in the between-condition changes has an effect on the estimation results, we performed a two-stage regression: On the first stage, only the "no load" trials were analyzed and only the two coefficients μ and σ were estimated, with random effects included in both of them and with the covariance between the random effects not being restricted to zero. On the second stage, the "load" trials were analyzed, with δ_μ being estimated as the term hat has to be added to $\hat{\mu}$—including the respective individual random effects—estimated on the first stage to explain behavior in the "load" trials. The same applies to δ_σ. Again, the covariance between the random effects was not restricted to zero. Accounting for simultaneous between-subject variability in all parameters in this way does not change the finding of significantly increased risk aversion under load, but it worsens the BIC. We, therefore, proceed on the basis of Regression CARA that included random effects only in μ.

Table 2. Results of the extended structural regressions.

	CARA Ext. 1		CARA Ext. 2		CARA Ext. 3		CARA Ext. 4	
Coefficient	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
$\hat{\mu}$	0.0925	0.000	0.0911	0.000	0.0945	0.000	0.0932	0.000
$\hat{\delta}_\mu$	0.0106	0.007	0.0095	0.017	0.0110	0.005	0.0136	0.001
$\hat{\gamma}_{\mathrm{SP},\mu}$	0.0493	0.000	0.0480	0.000	0.0524	0.000	0.0536	0.000
$\hat{\gamma}_{\mathrm{CL}\times\mathrm{SP},\mu}$	−0.0030	0.752	−0.0024	0.799	0.0019	0.843	0.0116	0.240
$\hat{\gamma}_{\mathrm{RT},\mu}$	—		−0.0028	0.027	−0.0002	0.903	−0.0005	0.723
$\hat{\gamma}_{\mathrm{WM},\mu}$	—		—		—		−0.0008	0.000
$\hat{\sigma}$	0.7330	0.000	0.7263	0.000	0.7263	0.000	0.7264	0.000
$\hat{\delta}_\sigma$	−0.0368	0.524	−0.0356	0.535	0.0924	0.081	0.0803	0.122
$\hat{\gamma}_{\mathrm{SP},\sigma}$	0.0540	0.683	0.0557	0.670	0.1253	0.271	0.1578	0.000
$\hat{\gamma}_{\mathrm{CL}\times\mathrm{SP},\sigma}$	−0.2217	0.184	−0.2240	0.174	−0.1423	0.334	−0.1032	0.323
$\hat{\gamma}_{\mathrm{RT},\sigma}$	—		—		0.2068	0.000	0.2121	0.000
$\hat{\gamma}_{\mathrm{WM},\sigma}$	—		—		—		−0.0039	0.116
BIC	5,357.2		5,359.0		5,245.7		5,244.4	

Notes: Estimates based on $T = 4{,}914$ choices by $N = 41$ subjects. Non-linear maximum likelihood estimation, all subjects pooled, allowing for between-subject heterogeneity in μ via individual random effects. The estimation was performed with MATLAB R2013a, using the `nlmefit` function. "BIC": Bayesian Information Criterion, calculated as $-2\,\ell(\hat{\rho}, \hat{\delta}_\rho, \hat{\sigma}, \hat{\delta}_\sigma) + k \ln N$, where N is the number of subjects ($N = 41$), and k is the number of fitting parameters; here $k = 9$, 10, 11, and 13, respectively.

4.3.3 Extended Structural Regression 1: Influence of the Presence of a Sure Payoff

The purpose of extending the structural regressions by including additional explanatory variables is twofold: (i) to test the theoretical prediction that sure payoffs are particularly attractive and (ii) to address the variation in subjects' response times reported above. That is, we included additional trial-specific regressors such as the presence of a sure payoff, response times, and the difficulty of the working-memory task. All additional regressors were mean-centered, such that $\hat{\mu}$ continues to indicate the average degree of absolute risk aversion in the "no load" condition and $\hat{\delta}_\mu$ its change due to cognitive load.

To mention the central result upfront: $\hat{\delta}_\mu$ is significantly positive also when controlling for these additional factors; see Table 2, which reports the results of the extended structural regressions.

As the first additional regressor, we included in regression CARA Ext. 1 a dummy regressor that equals 1 if a sure payoff was present in trial t. We find that the associated coefficient $\hat{\gamma}_{\mathrm{SP},\mu}$ is positive and substantial. That is, the presence of a sure payoff led to a substantially larger expressed degree of risk aversion. In other words, a sure payoff seems to have been especially attractive to subjects. This is in line with the finding reported above that subjects avoided the riskier option particularly often in safe–risky trials, and it is consistent with the model by Fudenberg and Levine (2011).

To check whether a sure payoff is even more attractive under cognitive load, we interacted the "load" dummy regressor with the dummy regressor for the presence of a sure payoff. As in our earlier analysis of the frequency with which subjects chose the risky or the safe option, we do not find this interaction effect to be significant; the point estimate of the interaction effect, $\hat{\gamma}_{\text{CL}\times\text{SP},\mu}$, is virtually zero. In other words, the increase in risk aversion in the safe–risky trials is almost identical in size to the increase in risk aversion in the risky–risky trials. As a matter of fact, the load-induced increase of risk aversion in the safe–risky trials actually fails to reach significance according to our structural regressions—in contrast to what we found when analyzing the count data, i.e., the frequency with which subjects chose the safe or risky option.[16]

Result 6. *According to our structural regressions, safe payoffs are particularly attractive to subjects. However, cognitive load does not seem to increase this "certainty effect," in contrast to the prediction of the Fudenberg–Levine model.*

4.3.4 Extended Structural Regressions 2 and 3: Influence of Response Times

Based on our previous analysis of the relation between response times in the lottery choice task and performance in the working-memory task, we cannot rule out that cognitive load generates time pressure in the lottery choice task and influences risk attitudes via this channel. In order to assess to which extent the influence of cognitive load on risk attitudes operates through potential time pressure, we included subjects' deviation from their individual mean response time as a regressor.[17]

At first glance, response times and risk aversion seem to be related, with risk aversion being lower when subjects took more time to deliberate on their choice: The estimate $\hat{\gamma}_{\text{RT},\mu}$ is significantly negative in regression CARA Ext. 2. This is accompanied by a reduction of the direct effect of cognitive load measured by $\hat{\delta}_{\mu}$.

It is crucial, however, to include response times also in the Fechner noise term. This is because response times have long been recognized in psychology as an indicator of task difficulty. It has been found for comparative judgments across various perceptual domains that response times are "a negative linear function of the logarithm of the difference" of the magnitudes to be compared—e.g., the size of objects, their luminance, and even abstract numbers (see Chabris et al., 2009, p. 629, and the references therein; Milosavljevic et al., 2011). Hence, comparative judgments seem to be the more difficult, in the sense of more time-consuming, the more similar the values to be compared are.

[16] In contrast, when we exclude the safe–risky trials from the analysis—i.e., we analyze only the risky–risky trials—we still obtain a significant load-induced increase in risk aversion ($p = 0.0043$). This regression correctly predicts 72.65% of choices in the "no load" and 73.00% in the "load" condition. Just like in the respective regressions including both the safe–risky and the risky–risky trials, there is no cognitive-load–induced change in the Fechner noise term ($p = 0.8744$).

[17] Since between-subject variation in risk attitudes is captured by individual random effects, between-subject variation in response times can add no explanatory power even if a between-subject correlation between risk aversion and average response times actually exists. However, we are more interested in within-subject variation than in between-subject variation, because the latter is less informative with respect to causality: It might be that some third factor—e.g., age—causally influences both subjects' risk attitudes and their response times, so that causal statements based on between-subject statements are difficult.

A theoretical model that predits this very pattern of response times is the so-called drift–diffusion model (DDM) of the decision process (e.g., Ratcliff, 1978). A particular variant has entered the literature on decision making under risk in the form of decision field theory (Busemeyer and Townsend, 1993). The DDM has become increasingly popular due to the support it has found in neuroimaging studies (expositions for an economics audience can be found in Fehr and Rangel, 2011; Clithero and Rangel, 2013). We discuss the drift–diffusion model in greater detail in Section 5.

The idea captured by the DDM that a longer response time is a sign of a more difficult decision also serves as the basis of the analyses in Dohmen and Falk (2011, p. 580) and in Chabris et al. (2008, p. 7/8). These two studies as well as the study by Clithero and Rangel (2013) rest on the logic of reversely inferring that the available options are the closer in subjective valuation, the longer response times are. In our context, the V-difference should be the smaller, the longer it takes subjects to decide. Decreasing the V-difference that enters equation (1) can be achieved by increasing the denominator, i.e., the Fechner noise term.

Investigating a potential effect of this kind means to include response times as a regressor in the Fechner noise term (see regression CARA Ext. 3), with the prediction that the associated coefficient $\gamma_{\mathrm{RT},\sigma}$ is positive. When we do so, $\hat{\gamma}_{\mathrm{RT},\sigma}$ turns out to be significantly positive ($p < 0.001$), while no systematic relation between response times and risk aversion can be found anymore: The coefficient $\hat{\gamma}_{\mathrm{RT},\mu}$ shrinks drastically vis-à-vis CARA Ext. 2 and becomes insignificant ($p > 0.7$).[18] Importantly, the coefficient on the "load" dummy remains significant even when adding response times as a regressor for the Fechner noise.[19]

Result 7. *Cognitive load seems to affect risk attitudes directly and not only via (perceived) time pressure.*

In related research, Krajbich et al. (2015) showed that controlling for the relative valuation of the available options eliminates previously observed correlations between response times and particular types of decisions also in other domains of decision making. The absence of a relation between response times and risk attitudes that we find is in line with the results obtained by Kocher et al. (2013) who found no evidence for a systematic influence of time pressure on risk attitudes in the gain domain.

Our results indicate that the effects of cognitive load on risk attitudes may be partially due to a (perceived) time pressure that cognitive load generates, but that they are not restricted to this channel. It rather seems that the working-memory demands of the load task have an effect on risk attitudes on their own.

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[18] We obtain qualitatively the same result when including response times in the form of a factor $\mathrm{MRT}_s / \mathrm{RT}_{s,t}$ by which $\Delta\mathrm{CE}_{s,t}$ is multiplied. Here, s indexes subjects, t indexes trials, and MRT_s is the mean response time of subject s; note that this factor varies trial-by-trial around unity. Hence, it does not matter much whether the influence of response times enters the error term additively or multiplicatively.

[19] Conversely, when omitting the "load" dummy in the regression—i.e., when explaining the between-condition variation in risk attitudes via the response times alone—we found the following: As long as the response times are not included in the denominator, shorter response times go along with significantly increased risk aversion. When the response times are, however, also added as an explanatory variable to the Fechner noise, this relation becomes insignificant.

Table 3. Influence of the decision type and the V-difference on log response times in the lottery choice task.

Dependent variable: Log response time ($\ln \mathrm{RT}_{s,t}$)	Regression RT Ext. 1		Regression RT Ext. 2	
Regressor	Coefficient	p-value	Coefficient	p-value
Constant	1.1662	0.000	1.3141	0.000
$D_{\mathrm{RLC},s,t} \times D_{\mathrm{SP},t}$	—		−0.4254	0.000
$D_{\neg\mathrm{RLC},s,t} \times D_{\neg\mathrm{SP},s,t}$	—		−0.0276	0.647
$D_{\neg\mathrm{RLC},s,t} \times D_{\neg\mathrm{SP},s,t}$	—		−0.0692	0.348
$D_{\mathrm{CL},t}$	—		−0.1509	0.003
$D_{\mathrm{RLC},s,t} \times D_{\mathrm{SP},s,t} \times D_{\mathrm{CL},t}$	—		0.1057	0.141
$D_{\neg\mathrm{RLC},s,t} \times D_{\neg\mathrm{SP},s,t} \times D_{\mathrm{CL},t}$	—		0.0290	0.514
$D_{\neg\mathrm{RLC},s,t} \times D_{\neg\mathrm{SP},s,t} \times D_{\mathrm{CL},t}$	—		0.0467	0.396
$\lvert\Delta V_{s,t}\rvert$	−0.1078	0.000	−0.0818	0.000
Dummy per subject s	Yes		Yes	
BIC	4,101.1		3,823.8	

Notes: Estimates are based on choices in $T = 3{,}441$ trials (indexed t) by $N = 41$ subjects (indexed s). $D_{\mathrm{RLC},s,t}$ equals 1 if the riskier lottery was chosen by subject s in trial t and 0 otherwise; $D_{\neg\mathrm{RLC},s,t}$ vice versa. $D_{\mathrm{SP},s,t}$ equals 1 if a sure payoff was present in trial t of subject s and 0 otherwise; $D_{\neg\mathrm{SP},s,t}$ vice versa. $D_{\mathrm{CL},t}$ equals 1 if a sure payoff was present in trial t and 0 otherwise; $D_{\neg\mathrm{CL},t}$ vice versa. $\lvert\Delta V_{s,t}\rvert \equiv \lvert\Delta \mathrm{CE}_{s,t}\rvert$ as estimated by Regression CARA Ext. 2. Ordinary least-squares estimation, all subjects pooled. The estimation was performed with Stata/MP 13.1. Standard errors, and thus p-values, were adjusted for 41 clusters on the subject level. "BIC": Bayesian Information Criterion, calculated as $-2\ell + k \ln N$, where ℓ ist the log-likelihood, and k is the number of fitting parameters; here, $k = 42$ and 49, respectively.

4.3.5 Response Times: Control Regression Including the V-Difference as a Covariate

We are now in a position to augment the response time analysis reported in Section 4.2.1 to test whether response times are influenced by subjective valuation of the available options as predicted by the drift–diffusion model. Given the significantly negative estimates $\hat{\gamma}_{\mathrm{RT},\sigma}$ in Regression CARA Ext. 3 (and in CARA Ext. 4, see below), one would expect response times to be the longer, the more similar the two lotteries presented in a trial are in subjective valuation—in line with the predictions of the DDM.

To test this hypothesis, we augmented the regressions from Section 4.2.1 by including as an additional regressor the absolute value of the V-difference in trial t, $\lvert\Delta V_{s,t}\rvert$, as estimated by Regression CARA Ext. 2. Note that CARA Ext. 2 included response times as a determinant of the degree of risk aversion, μ, so that any correlation between $\lvert\Delta V_{s,t}\rvert$ and $\mathrm{RT}_{s,t}$ resulting from a potential influence of $\mathrm{RT}_{s,t}$ on $\lvert\Delta V_{s,t}\rvert$ through risk aversion has already been accounted for. Hence, any remaining correlation should be due to variation in the difficulty of the lottery choice. Note that $\Delta V_{s,t}$ varies between subjects based on the random effects included in the estimation of μ as well as trial-by-trial because of the changing lottery pairs.

The coefficient on $\lvert\Delta V_{s,t}\rvert$ is estimated to be negative and highly significant, see Table 3. This indicates that subjects responded the faster, the more the subjective valuation of the two lotteries presented in a trial differed from each other. More specifically, subjects responsed more than 300 ms faster when the difference between the certainty equivalents of the lotteries presented in a given trial increased by €1. This relation is as predicted by the DDM. Importantly, it is consistent with the negative estimate of the coefficient $\gamma_{\mathrm{RT},\sigma}$ when including response times as a determinant of the Fechner noise in Regressions CARA Ext. 3 and 4 (below).

Result 8. *The relation between the difference in subjective values of the lotteries included in a pair, $|\Delta V_{s,t}|$, and the response time in the respective trial is as predicted by the drift–diffusion model: The smaller $|\Delta V_{s,t}|$, the longer the response time.*

4.3.6 Extended Structural Regression 4: Cognitive Load—"On/Off" or Gradual Effect on Risk Aversion?

Finally, we included as a regressor the across-subject average hit rate for each arrangement of dots encountered in the cognitive-load task. This way, we proxy for trial-by-trial variation in the difficulty of the load task, i.e., the difficulty of remembering the specific arrangement of dots shown in trial t. This is possible because all subjects faced the same set of arrangements in the course of the experiment. Easier-to-remember arrangements are a proxy for lower cognitive load: Risk aversion should be the lower, the easier a trial's working-memory task—which would be expressed by a negative coefficient $\gamma_{\mathrm{WM},\mu}$. This is indeed what we find in regression CARA Ext. 4. Thus, cognitive load affects risk attitudes not in a mere "on/off" fashion but gradually, which further strengthens the evidence that cognitive load influences risk aversion.

Result 9. *Cognitive load affects risk attitudes in a gradual, and not a mere "on/off," fashion.*

5 Discussion

Using a standard repeated pairwise lottery choice task in combination with the presence or absence of a cognitively demanding distractor task in a within-subject design, we obtained the following results:

We find that additional cognitive load increases subjects' risk aversion. This finding is compatible with the dual-system approach, given that previous findings suggest that the emotional system steers decisions in the direction of increased risk aversion.

This interpretation is corroborated by the finding that response times in the lottery choice task were faster in the "cognitive load" condition than in the "no load" condition. It is also partially corroborated by the observation that even when controlling for the effect of the cognitive-load manipulation, subjects responded faster on average when choosing the safe than when choosing the risky alternative in safe–risky trials.

A similar response time pattern was already observed between subjects by Rubinstein (2007, 2013). Our within-subject findings can be seen as strengthening his interpretation that risk aversion is partially the consequence of "instinctive reasoning" by ruling out potential between-subject confounds. Moreover, our observation of particularly fast responses when the safe payoff is chosen is in line with the results of Koop and Johnson

(2013) who used a method called "mouse tracking" to investigate the choice process in pairwise lottery choice. In their study, each pair of two-outcome lotteries included a "safe alternative," by which the authors refer to a lottery whose larger payoff had a probability of 90%. Koop and Johnson (Fig. 7, p. 164) observed for the gain domain that when subjects chose the "risky" lottery, the average trajectory of their mouse movements initially pointed in the direction of the "safe" alternative before reverting in the direction of the "risky" alternative. In contrast, it was a unidirectional movement when the "safe" alternative was chosen. This provides additional evidence that safe gains exert a particular attraction, especially at the initial stages of the choice process.

Our results confirm and extend the results reported by Benjamin et al. (2013) who found a significant increase of risk aversion under cognitive load only for a subset of the choices that their subjects had made: for risky–risky trials, but not for safe–risky trials—with the point estimate for the safe–risky trials nevertheless being of the same sign. An explanation for the lack of a significant finding for the safe–risky trials in their study may be the combination of a rather low number of trials with a ceiling effect: just like in our study, their subjects showed pronounced risk aversion in safe–risky trials even in the absence of load, so that there is not much room for cognitive load to increase risk aversion even further. In contrast to Benjamin et al., we actually find stronger evidence that cognitive load increases risk aversion in the safe–risky trials than in the risky–risky trials when we use the count measure of how often subjects chose the less risky option (Section 4.1). This is also in line with the theoretical predictions of Fudenberg and Levine (2011).[20] However, in the complementary analysis via structural regressions, we observe a significant load-induced increase in risk aversion only when pooling the risky–risky and the safe–risky trials or when analyzing the risky–risky trials alone (4.3.2). Even though the point estimates for the load-induced increases in risk aversion are virtually identical in the safe–risky and the risky–risky trials, the effect does not reach significance in the safe–risky trials—similar to the results of Benjamin et al.

Of course, alternative explanations might be brought forward. We now address two of them, before outlining our preferred interpretation—which is that drift–diffusion models should be combined with the dual-system approach.

5.1 Is It Possible That the Cognitive-Load Manipulation Changed the Perceived Riskiness of the Presented Lotteries Rather Than Risk Preferences?

To be compatible with our findings, such a change in the perceived riskiness would have to put the riskier lottery at a disadvantage under cognitive load. This might happen if subjects focussed less on the lotteries' overall characteristics (say, their expected values) but more on their components (e.g., their minimum payoffs), and if they chose the lottery that

[20] One might argue that since our experiment used rather small stakes, it is not really capable of testing the Fudenberg and Levine (2011) model. From this point of view, our findings show that there has to exist an additional channel through which cognitive load influences risk attitudes, because we observe cognitive load to increase risk aversion even for payoffs so small that the Fudenberg–Levine model would predict no effect.

maximized the minimum possible outcome (a maxmin strategy like Gilboa and Schmeidler, 1989, suggest for decision making under ambiguity).

If the latter was true, one would expect the cognitive-load manipulation to cause a rather dramatic increase in the measured degree of risk aversion, because the lottery with the larger minimum payoff would be chosen regardless of its further properties. This is not what we observe.

The perceived relative riskiness of the presented lotteries could also be changed under cognitive load due to added noise in the processing of the lotteries' characteristics. If the perceived relative riskiness was influenced by cognitive load to the disadvantage of the riskier option, we would expect this effect to be especially pronounced in those trials in which a sure payoff was present.

A similar hypothesis would be that subjects have a "preference for simplicity" that gets strengthened by cognitive load. While we cannot completely rule out that such a factor is at work, they cannot be the whole story, since we find a significant increase in risk aversion also in the risky–risky trials. Increased (perceived) noise in subjects' processing should probably also be reflected in the consistency of subjects' choices, i.e., the Fechner noise term should increase under cognitive load. However, our structural regressions yield no evidence for such an effect. Let us, hence, turn to our preferred interpretation.

5.2 Could Decision Field Theory or Similar Drift–Diffusion Models Explain Our Results Regarding Choices and Response Times?

Drift–diffusion models are models of the decision making *process* (for a review targeted at an economics audience, see Fehr and Rangel, 2011). The central assumption is that a decision between the available alternatives is made by noisy accumulation of evidence, through sequential sampling, in favor of each of the alternatives. The average rate of accumulation is called the "drift rate" for the respective decision. A decision in favor of a particular alternative is made once a threshold associated with that alternative, the "decision boundary," is reached. For a graphical illustration of a two-alternative drift–diffusion process, see Figure 5. According to the particular realization in the illustration, the less risky lottery would have been chosen as the result of 17 sequential-sampling steps.

Drift–diffusion models have originally been used to describe perceptual decision making and have been found to simultaneously account well for decisions, response times, and brain activity—the latter consistently so across different measures of neural activity (Heekeren et al., 2004). Importantly, recent studies found that also choices and brain activation during reward-based decision making are described well by this class of models (e.g., Basten et al., 2010; Heekeren et al., 2008).

An application of the drift–diffusion framework to decision making under risk is decision field theory (Busemeyer and Townsend, 1993).[21] In decision field theory, for a given set

[21] Decision field theory has been found to be successful, in the sense that it is able to "explain most effects [violations of expected utility theory], except violations of weak stochastic transitivity" (Rieskamp et al., 2006, p. 649) while being relatively parsimonious, i.e., requiring relatively few parameters.

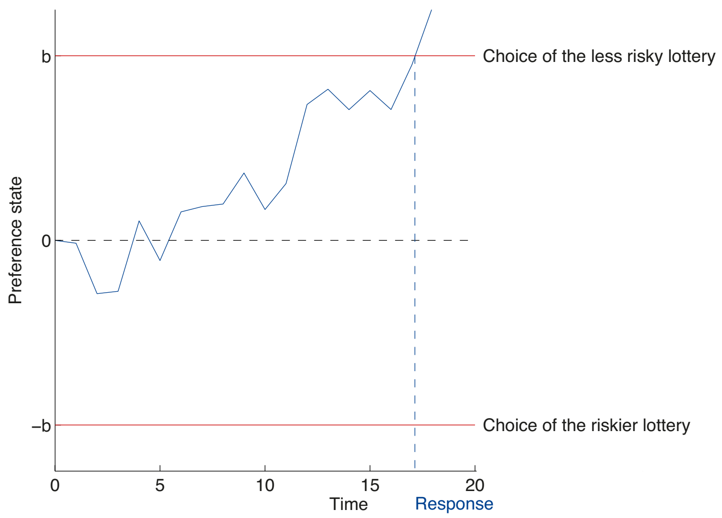

Figure 5. Illustration of a drift–diffusion process, adapted from Busemeyer and Townsend (1993, Figure 6).

of lottery pairs, the across-trial average drift rate towards the less risky alternative may be higher than that towards the riskier alternative. This is because the drift rates depend on agents' risk attitudes (see "Stage 3" and Formulas 2a and 2b of Busemeyer and Townsend, 1993). This would predict choices of the less risky alternative to be faster on average than choices of the riskier alternative—without reliance on dual decision processes. There exists a second possibility of generating asymmetric response times in the framework of decision field theory: It could be that the starting point of the evaluation is biased, i.e., it is closer to one decision boundary than to the other. (Figure 5 depicts the unbiased situation.)

The influence of cognitive load on subjects' behavior that we observe can be explained as follows: The decision boundaries are more liberal (closer to each other) under cognitive load, leading to faster responses for both types of choices in the "load" condition—probably, to free up resources in order to perform well in the working-memory task, see Section 4.2.1. With a bias in favor of the less risky lottery, more liberal decision boundaries under load lead to more risk-avoiding choices, since a narrower corridor effectively strengthens the bias. In this way, the drift–diffusion model can explain our findings without resorting to a dual-process account. It can, moreover, explain the observation that the estimated coefficient on the V-difference is negative in the response time regression (Section 4.3.4), since a low $|\Delta V|$ implies weak drift.

It is important to note, however, that none of the above effects can be derived purely *within* decision field theory and similar drift–diffusion models. These models make no predictions on changes due to cognitive load. Changes to the models' parameters must be introduced exogenously—so we are essentially back at a dual-process explanation. Moreover, it is unclear how the results from lesion studies (Hsu et al., 2005; Shiv et al., 2005) could be explained in a drift–diffusion framework without modification. Those results indicate that the inputs to the accumulation of evidence in favor of the one or the other gamble are, at least partially, of an emotional kind.

Hence, there is room for a dual-process interpretation in combination with drift–diffusion models. The strength of drift–diffusion models lies in the detailed description of the decision-making process; but they do not necessarily make predictions concerning the circumstances under which a change in the process should occur. By contrast, dual-process theories make predictions concerning the factors that should influence decision making, but often remain silent on how exactly the decision-making process works. We therefore consider the two rather as complementary than as competing approaches. In this spirit, a formalization of the interplay of cognition and emotion in the form of two interacting information-accumulating processes has recently been proposed by Achtziger and Alós-Ferrer (2014).

Alternatively, it might be that attention in the attention-augmented drift–diffusion model (Krajbich et al., 2010; Hare et al., 2011) evolves in a systematic way. This would mean that evidence in favor of picking either alternative is not accumulated in random order; instead, in early sequential-sampling steps, evidence in favor of avoiding the riskier option is attended to preferentially and receives higher weight—especially so when a completely (or close to) safe alternative is present. While accumulation in random order predicts fluctuations in the preference state with a monotonic drift, the latter variant predicts accumulation that is initially biased in the direction of avoiding risk, before at times reverting such that the riskier alternative is chosen (as reflected in the mouse trajectories presented by Koop and Johnson, 2013, Fig. 7, p. 164). This early focus on avoiding risk may be the outcome of quick, upstream affective processing that feeds into the sequential sampling process and thereby influences in particular the early steps of the choice process.

5.3 Conclusion

Our within-subject findings strengthen the evidence that cognitive load induces a change in risk attitudes. They confirm the between-subject results reported by Benjamin et al. (2013) and strengthen them in an important way. Furthermore, our within-subject findings on response times provide a basis for Rubinstein's (2007) claim that risk aversion is, in part, generated by "instinctive reasoning." By also supporting the dual-self model proposed by Fudenberg and Levine (2006, 2011), our findings endorse the common underlying idea: to explore decision making under risk with the help of the dual-system approach.

Concerning the relevance of our findings, however, the exact mechanism is not crucial. Our findings suggest a systematic variation in how people make economic decisions: their preferences seem to interact with the complexity of the decision environment. As an example, price volatility on stock and foreign-exchange markets is known to change substantially over time. Our results suggest that investors' decisions might differ systematically between the different volatility regimes. Specifically, if during times of high volatility, investors process more information and make more decisions than during times of low volatility, their risk aversion may be greater in volatile times. Following the same logic, we would expect systematic differences between decisions that people make at the workplace, depending on the number and complexity of the projects that they work on simultaneously. More generally, the more complex the available options or the choice menu, the more frequently seemingly low-risk options should be chosen (although there exists contradictory evidence concerning the so-called "choice overload" hypothesis).

These hypotheses are, admittedly, speculative. We look forward to testing them in future research.

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Appendix A Supplementary Tables and Figures

Table A.1. The 60 lottery pairs presented in the two conditions.

No.	Lottery $\boldsymbol{A}$			Lottery $\boldsymbol{B}$			$\boldsymbol{A} \succ \boldsymbol{B}$	$\boldsymbol{A} \succ \boldsymbol{B}$
	$x_{\boldsymbol{A},1}$	$x_{\boldsymbol{A},2}$	$p_{\boldsymbol{A},1}$	$x_{\boldsymbol{B},1}$	$x_{\boldsymbol{B},2}$	$p_{\boldsymbol{B},1}$	for $\mu <$	for $\rho <$
1	3	15	0.50	5	10	0.25	0.0160	0.1307
2	3	15	0.50	6	9	0.10	0.0171	0.1383
3	7	12	0.75	8	10	0.90	0.0236	0.2112
4	5	10	0.25	6	9	0.10	0.0253	0.1946
5	3	15	0.50	7	9	0.25	0.0285	0.2275
6	2	20	0.50	4	12	0.25	0.0296	0.2662
7	2	20	0.75	3	15	0.75	0.0341	0.2619
8	6	15	0.75	8	8	1.00	0.0348	0.3212
9	6	15	0.75	7	9	0.50	0.0375	0.3509
10	2	20	0.75	5	10	0.90	0.0389	0.2828
11	2	20	0.50	5	10	0.10	0.0389	0.3387
12	8	15	0.75	6	10	0.10	0.0415	0.4698
13	3	15	0.50	6	9	0.25	0.0443	0.3478
14	3	15	0.75	5	10	0.90	0.0446	0.3071
15	3	15	0.50	8	10	0.90	0.0454	0.3556
16	6	12	0.50	7	9	0.10	0.0465	0.4067
17	3	15	0.50	7	12	0.75	0.0484	0.3715
18	6	15	0.75	6	10	0.50	0.0498	0.4936
19	3	15	0.50	8	8	1.00	0.0566	0.4379
20	3	15	0.50	7	9	0.50	0.0583	0.4499
21	4	12	0.10	11	11	1.00	0.0610	0.5159
22	2	20	0.10	17	17	1.00	0.0615	0.6493
23	3	15	0.25	11	11	1.00	0.0661	0.5699
24	4	12	0.50	7	9	0.75	0.0663	0.4881
25	3	15	0.25	4	12	0.10	0.0676	0.5853
26	4	12	0.25	6	10	0.10	0.0696	0.5552
27	3	15	0.50	6	15	0.75	0.0700	0.4903
28	2	20	0.25	13	13	1.00	0.0702	0.6648
29	6	9	0.25	8	10	0.90	0.0714	0.5326
30	4	12	0.50	7	12	0.90	0.0728	0.5250
31	4	12	0.50	6	9	0.50	0.0739	0.5427
32	6	12	0.50	6	9	0.10	0.0744	0.6525
33	3	15	0.50	7	9	0.75	0.0891	0.6642
34	3	15	0.10	13	13	1.00	0.0923	0.8358
35	4	12	0.25	5	10	0.10	0.0925	0.7355
36	3	15	0.50	7	12	0.90	0.0929	0.6854
37	3	15	0.50	6	9	0.50	0.0937	0.6962
38	4	12	0.25	8	15	0.75	0.0953	0.6022
39	2	20	0.50	7	9	0.75	0.0978	0.7463
40	4	12	0.25	9	13	0.90	0.0988	0.7673
41	2	20	0.50	7	12	0.90	0.1000	0.7575
42	2	20	0.50	6	9	0.50	0.1005	0.7634
43	2	20	0.50	3	15	0.50	0.1081	0.8245
44	2	20	0.50	4	12	0.50	0.1089	0.8204
45	3	15	0.50	4	12	0.50	0.1103	0.8123
46	5	10	0.25	7	9	0.25	0.1154	0.8675
47	5	10	0.10	9	13	0.90	0.1374	0.9526
48	3	15	0.75	4	15	0.90	0.1497	0.8958
49	6	11	0.25	4	7	0.10	$\boldsymbol{A} \succ_{\text{SSD}} \boldsymbol{B}$	
50	6	12	0.75	4	7	0.50	$\boldsymbol{A} \succ_{\text{SSD}} \boldsymbol{B}$	
51	6	11	0.50	3	8	0.25	$\boldsymbol{A} \succ_{\text{SSD}} \boldsymbol{B}$	
52	6	11	0.75	3	8	0.50	$\boldsymbol{A} \succ_{\text{SSD}} \boldsymbol{B}$	
53	6	8	0.50	3	5	0.50	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
54	6	9	0.75	4	9	0.75	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
55	5	9	0.50	4	8	0.75	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
56	5	5	1.00	3	5	0.75	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
57	5	7	0.50	4	6	0.50	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
58	4	6	0.25	3	5	0.25	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
59	5	8	0.10	5	8	0.90	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	
60	5	7	0.50	4	6	0.75	$\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$	

Notes: $\boldsymbol{A} \succ_{\text{FSD}} \boldsymbol{B}$ indicates first-order stochastic dominance and $\boldsymbol{A} \succ_{\text{SSD}} \boldsymbol{B}$ second-order stochastic dominance of $\boldsymbol{A}$ over $\boldsymbol{B}$. The column "$\boldsymbol{A} \succ \boldsymbol{B}$ for $\mu <$" refers to exponential (CARA) utility $u^{\text{exp}}(x;\mu) \equiv (1 - \mathrm{e}^{-\mu x})/\mu$, while "$\boldsymbol{A} \succ \boldsymbol{B}$ for $\rho <$" refers to power (CRRA) utility $u^{\text{pow}}(x;\rho) \equiv (x^{1-\rho} - 1)/(1-\rho)$.

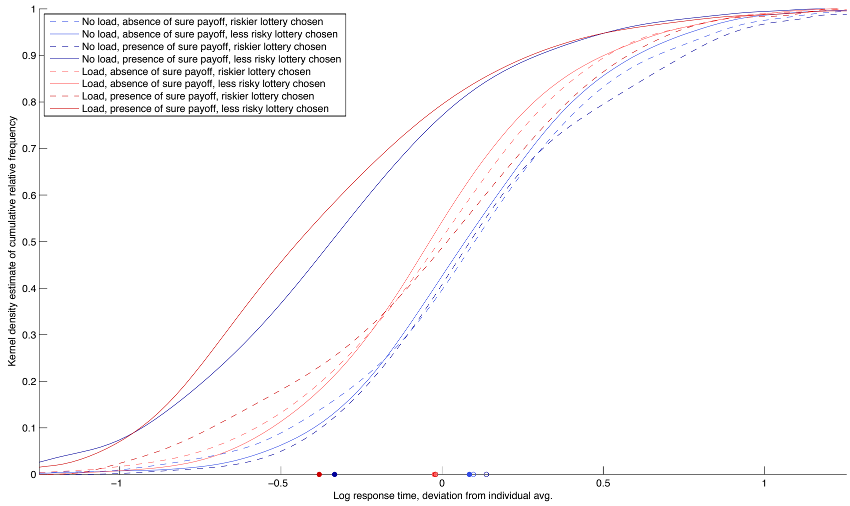


Figure A.1. Cumulative distributions of the log response times in the lottery choice task (within-subject variation, i.e., deviation from the individual average log response time): load / no load × presence / absence of sure payoff × risky / less risky alternative chosen.

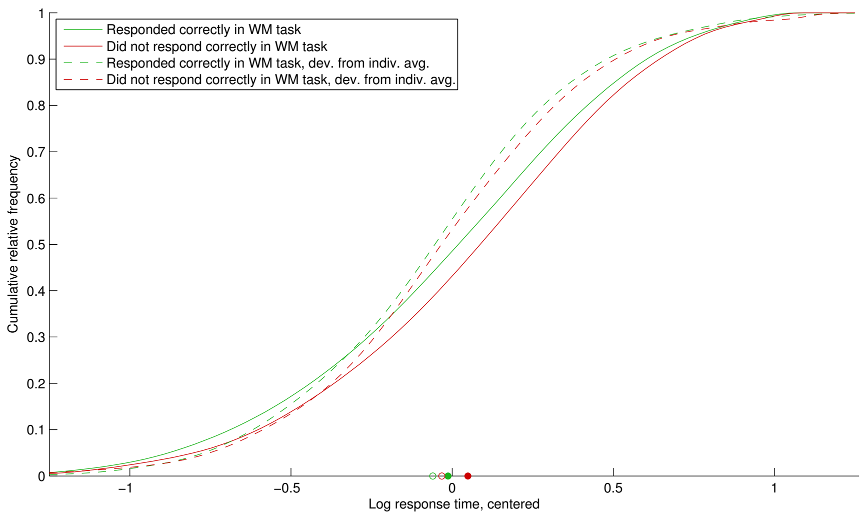


Figure A.2. Cumulative distribution of the centered log response times in the lottery choice task, depending on a correct or incorrect response in the working-memory task.

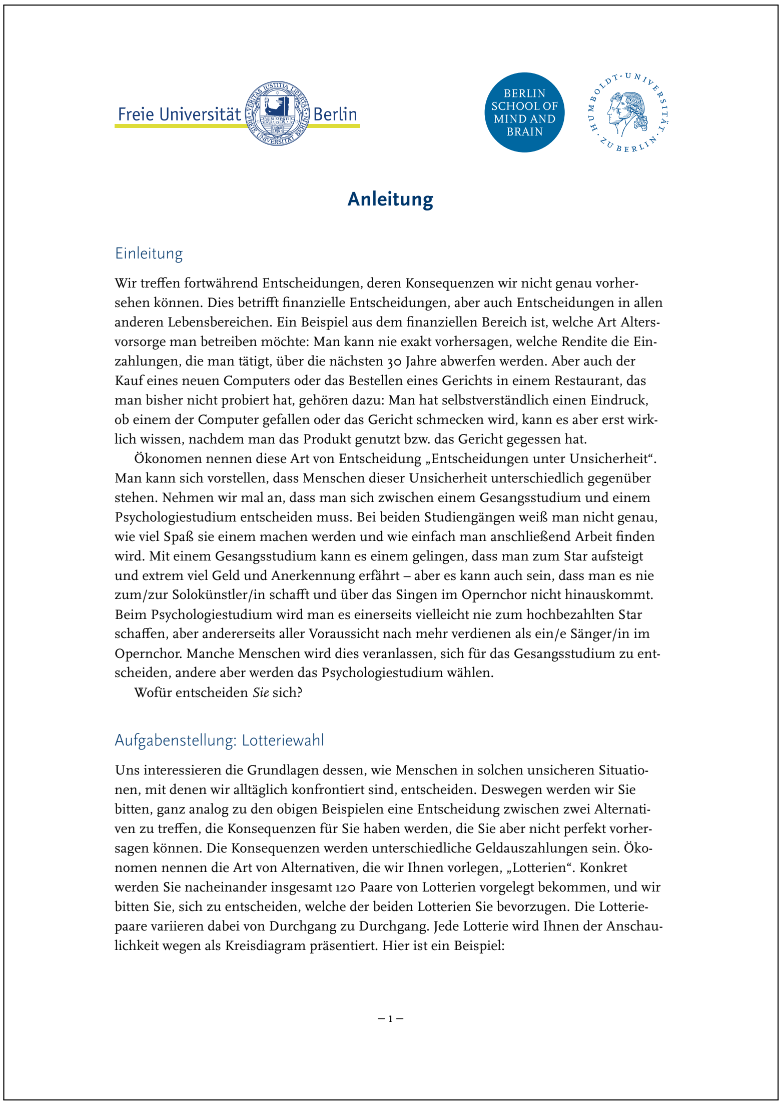
Appendix B Translation of the Instructions

Introduction

We continuously make decisions the consequences of which we cannot foretell exactly. This concerns financial decisions but also decisions in all other areas of our lives. An example from the financial domain is the kind of provision for one's old age that one desires: one can never forecast exactly the return that one's retirement savings will bear over the next 30 years. Also buying a new computer or ordering a meal in a restaurant that one has not tried yet are decisions of this kind: of course, one has an impression whether the computer will suit one's needs or whether the meal will be to one's liking, but one can only know for sure after one has used the product or eaten the meal, respectively.

Economists call this type of decision "decisions under uncertainty." It is conceivable that humans confront the described uncertainty in different ways. Imagine that you had to decide between studying voice and opera performance and studying psychology. For both courses of studies, one does not know in advance how much one will enjoy them and whether one will find a job subsequently. When studying voice, one might make it and become a star, earn extreme amounts of money, and receive a lot of approval—it might, however, also happen that one will never succeed to become a soloist and one will not advance beyond being a member of the opera choir. When studying psychology, one will, on the one hand, probably never succeed to become a highly paid star, but, on the other hand, one will by all chances have a better income than a singer in the opera choir. These prospects will induce some people to study voice, while others will choose to study psychology.

What is your decision?


Freie Universität Berlin

BERLIN SCHOOL OF MIND AND BRAIN

Anleitung

Einleitung

Wir treffen fortwährend Entscheidungen, deren Konsequenzen wir nicht genau vorhersehen können. Dies betrifft finanzielle Entscheidungen, aber auch Entscheidungen in allen anderen Lebensbereichen. Ein Beispiel aus dem finanziellen Bereich ist, welche Art Altersvorsorge man betreiben möchte: Man kann nie exakt vorhersagen, welche Rendite die Einzahlungen, die man tätigt, über die nächsten 30 Jahre abwerfen werden. Aber auch der Kauf eines neuen Computers oder das Bestellen eines Gerichts in einem Restaurant, das man bisher nicht probiert hat, gehören dazu: Man hat selbstverständlich einen Eindruck, ob einem der Computer gefallen oder das Gericht schmecken wird, kann es aber erst wirklich wissen, nachdem man das Produkt genutzt bzw. das Gericht gegessen hat.

Ökonomen nennen diese Art von Entscheidung „Entscheidungen unter Unsicherheit“. Man kann sich vorstellen, dass Menschen dieser Unsicherheit unterschiedlich gegenüber stehen. Nehmen wir mal an, dass man sich zwischen einem Gesangsstudium und einem Psychologiestudium entscheiden muss. Bei beiden Studiengängen weiß man nicht genau, wie viel Spaß sie einem machen werden und wie einfach man anschließend Arbeit finden wird. Mit einem Gesangsstudium kann es einem gelingen, dass man zum Star aufsteigt und extrem viel Geld und Anerkennung erfährt – aber es kann auch sein, dass man es nie zum/zur Solokünstler/in schafft und über das Singen im Opernchor nicht hinauskommt. Beim Psychologiestudium wird man es einerseits vielleicht nie zum hochbezahlten Star schaffen, aber andererseits aller Voraussicht nach mehr verdienen als ein/e Sänger/in im Opernchor. Manche Menschen wird dies veranlassen, sich für das Gesangsstudium zu entscheiden, andere aber werden das Psychologiestudium wählen.

Wofür entscheiden *Sie* sich?

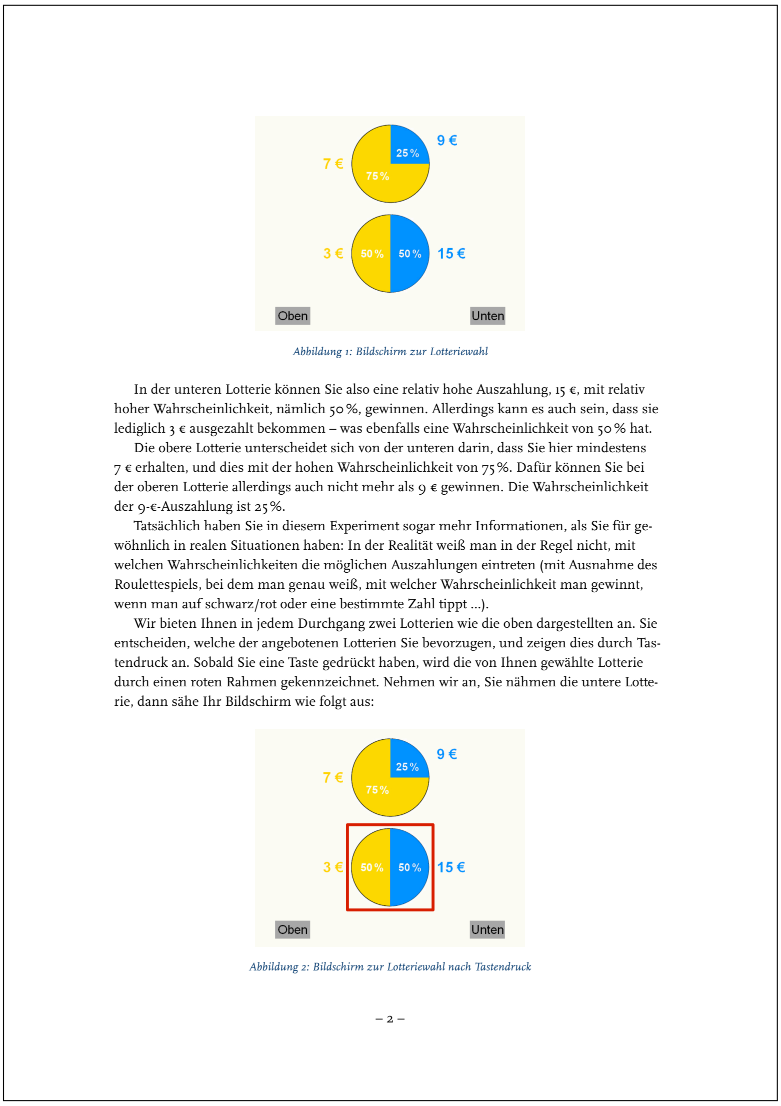
Aufgabenstellung: Lotteriewahl

Uns interessieren die Grundlagen dessen, wie Menschen in solchen unsicheren Situationen, mit denen wir alltäglich konfrontiert sind, entscheiden. Deswegen werden wir Sie bitten, ganz analog zu den obigen Beispielen eine Entscheidung zwischen zwei Alternativen zu treffen, die Konsequenzen für Sie haben werden, die Sie aber nicht perfekt vorhersagen können. Die Konsequenzen werden unterschiedliche Geldauszahlungen sein. Ökonomen nennen die Art von Alternativen, die wir Ihnen vorlegen, „Lotterien“. Konkret werden Sie nacheinander insgesamt 120 Paare von Lotterien vorgelegt bekommen, und wir bitten Sie, sich zu entscheiden, welche der beiden Lotterien Sie bevorzugen. Die Lotteriepaare variieren dabei von Durchgang zu Durchgang. Jede Lotterie wird Ihnen der Anschaulichkeit wegen als Kreisdiagram präsentiert. Hier ist ein Beispiel:

– 1 –

Your Task: Lottery Choice

We are interested in the foundations of how people decide in such uncertain situations as we face them day in, day out. For this reason, we ask you, in analogue to the above examples, to make a decision between two alternatives. The alternatives will have consequences for you, but you are unable to predict them perfectly. The consequences will be monetary payoffs of varying sizes. Economists call the type of alternatives that you will be presented "lotteries." Specifically, we will present you, sequentially, a total of 120 pairs of lotteries, and we will ask you to decide each time which of the two lotteries you prefer. The lottery pairs vary from round to round. For your convenience, each lottery will be illustrated by a pie chart. Here is an example:



7 €
25 %
75 %
9 €
3 €
50 %
50 %
15 €
Oben
Unten

Abbildung 1: Bildschirm zur Lotteriewahl

In der unteren Lotterie können Sie also eine relativ hohe Auszahlung, 15 €, mit relativ hoher Wahrscheinlichkeit, nämlich 50 %, gewinnen. Allerdings kann es auch sein, dass sie lediglich 3 € ausgezahlt bekommen – was ebenfalls eine Wahrscheinlichkeit von 50 % hat.

Die obere Lotterie unterscheidet sich von der unteren darin, dass Sie hier mindestens 7 € erhalten, und dies mit der hohen Wahrscheinlichkeit von 75 %. Dafür können Sie bei der oberen Lotterie allerdings auch nicht mehr als 9 € gewinnen. Die Wahrscheinlichkeit der 9-€-Auszahlung ist 25 %.

Tatsächlich haben Sie in diesem Experiment sogar mehr Informationen, als Sie für gewöhnlich in realen Situationen haben: In der Realität weiß man in der Regel nicht, mit welchen Wahrscheinlichkeiten die möglichen Auszahlungen eintreten (mit Ausnahme des Roulettespiels, bei dem man genau weiß, mit welcher Wahrscheinlichkeit man gewinnt, wenn man auf schwarz/rot oder eine bestimmte Zahl tippt ...).

Wir bieten Ihnen in jedem Durchgang zwei Lotterien wie die oben dargestellten an. Sie entscheiden, welche der angebotenen Lotterien Sie bevorzugen, und zeigen dies durch Tastendruck an. Sobald Sie eine Taste gedrückt haben, wird die von Ihnen gewählte Lotterie durch einen roten Rahmen gekennzeichnet. Nehmen wir an, Sie nähmen die untere Lotterie, dann sähe Ihr Bildschirm wie folgt aus:

7 €
25 %
75 %
9 €
3 €
50 %
50 %
15 €
Oben
Unten

Abbildung 2: Bildschirm zur Lotteriewahl nach Tastendruck

– 2 –

[Figure 1. Decision screen for the lottery choice]

With the lottery at the bottom, you can gain a comparatively large payoff, €15, with a relatively high likelihood, 50%. However, it can also happen that your payoff will be only €3—which also has 50% probability.

The lottery at the top differs from the lower one in that it pays at least €7, and that this has a high likelihood of 75%. In exchange for this, you cannot win more than €9 with the lottery at the top. The probability of the €9 payoff is 25%.

As a matter of fact, in this experiment you are given more information than you commonly have in real-life situations: In reality, one typically does not know the probabilities at which particular payoffs will realize themselves (an exemption is playing roulette, where the probability of winning is completely fixed when betting on red/black oder a particular number . . .).

In every round, we offer you two lotteries like the ones depicted above. You decide which of the offered lotteries you prefer and indicate this by pressing a key. As soon as you have pressed a key, the lottery selected by you is highlighted by a red frame. Let us assume that you chose the bottom lottery; then your decision screen would look like this:

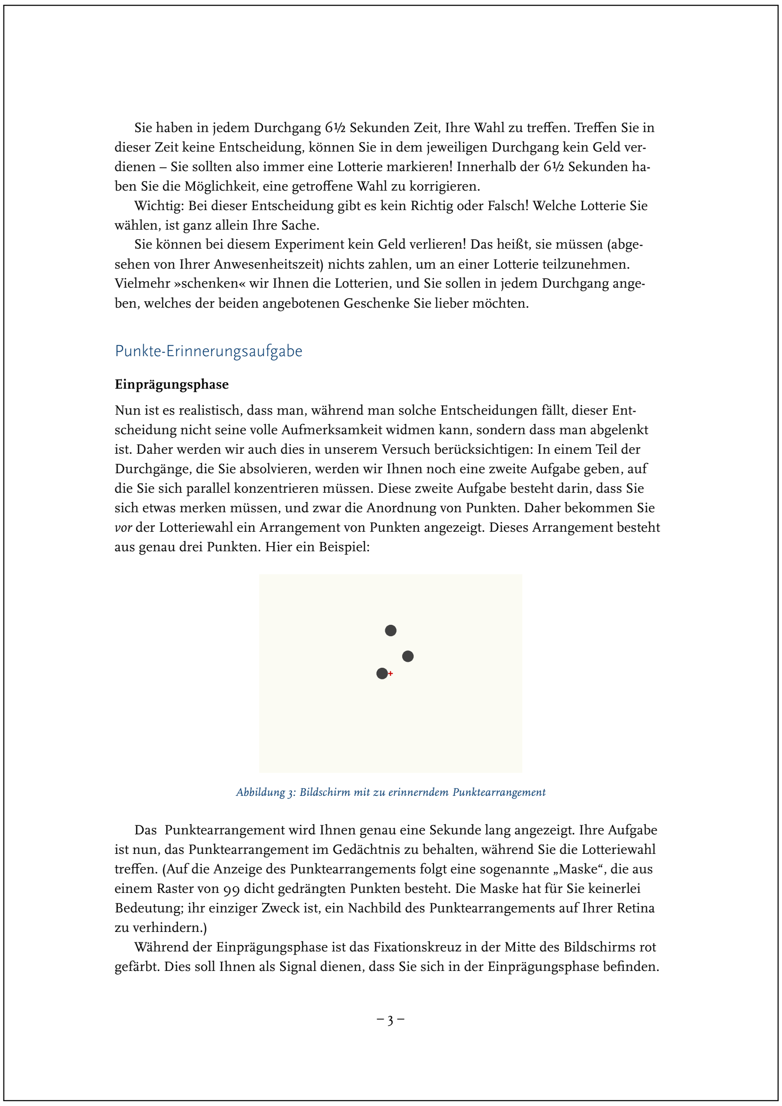
[Figure 2. Decision screen for the lottery choice after key press]

In each round, you are given 6½ seconds to make your choice. If you do not make a decision within this time frame, you cannot earn any money in that round—hence, you should select a lottery in every single trial! Within the 6½-second time frame, you have the opportunity to correct the choice that you have made.

Importantly, there is no right or wrong in such decisions! Whichever lottery you choose, is only up to you.

There is no way for you to lose any money in this experiment! That is, you do not have to pay anything (apart from your time of being here) to participate in a lottery. Rather, we give you the lottery as a "present," and in each round you are supposed to indicate which of the two offered presents you like better.

Dot Memorization Task



Sie haben in jedem Durchgang 6½ Sekunden Zeit, Ihre Wahl zu treffen. Treffen Sie in dieser Zeit keine Entscheidung, können Sie in dem jeweiligen Durchgang kein Geld verdienen – Sie sollten also immer eine Lotterie markieren! Innerhalb der 6½ Sekunden haben Sie die Möglichkeit, eine getroffene Wahl zu korrigieren.

Wichtig: Bei dieser Entscheidung gibt es kein Richtig oder Falsch! Welche Lotterie Sie wählen, ist ganz allein Ihre Sache.

Sie können bei diesem Experiment kein Geld verlieren! Das heißt, sie müssen (abgesehen von Ihrer Anwesenheitszeit) nichts zahlen, um an einer Lotterie teilzunehmen. Vielmehr »schenken« wir Ihnen die Lotterien, und Sie sollen in jedem Durchgang angeben, welches der beiden angebotenen Geschenke Sie lieber möchten.

Punkte-Erinnerungsaufgabe

Einprägungsphase

Nun ist es realistisch, dass man, während man solche Entscheidungen fällt, dieser Entscheidung nicht seine volle Aufmerksamkeit widmen kann, sondern dass man abgelenkt ist. Daher werden wir auch dies in unserem Versuch berücksichtigen: In einem Teil der Durchgänge, die Sie absolvieren, werden wir Ihnen noch eine zweite Aufgabe geben, auf die Sie sich parallel konzentrieren müssen. Diese zweite Aufgabe besteht darin, dass Sie sich etwas merken müssen, und zwar die Anordnung von Punkten. Daher bekommen Sie *vor* der Lotteriewahl ein Arrangement von Punkten angezeigt. Dieses Arrangement besteht aus genau drei Punkten. Hier ein Beispiel:

Abbildung 3: Bildschirm mit zu erinnerndem Punktearrangement

Das Punktearrangement wird Ihnen genau eine Sekunde lang angezeigt. Ihre Aufgabe ist nun, das Punktearrangement im Gedächtnis zu behalten, während Sie die Lotteriewahl treffen. (Auf die Anzeige des Punktearrangements folgt eine sogenannte „Maske", die aus einem Raster von 99 dicht gedrängten Punkten besteht. Die Maske hat für Sie keinerlei Bedeutung; ihr einziger Zweck ist, ein Nachbild des Punktearrangements auf Ihrer Retina zu verhindern.)

Während der Einprägungsphase ist das Fixationskreuz in der Mitte des Bildschirms rot gefärbt. Dies soll Ihnen als Signal dienen, dass Sie sich in der Einprägungsphase befinden.

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Memorizing Phase

Realistically, we cannot always devote our undivided attention to a decision that we are currently making; it might happen that we are being distracted. We will therefore take this into account in our study. In some of the rounds that you complete, we will add a second task that you will have to concentrate upon simultaneously. This second task requires you to memorize and remember something: the arrangement of several dots. More specifically, you will be shown an arrangement of dots *before* making the lottery choice. Each arrangement is composed of exactly three dots. Here is an example:

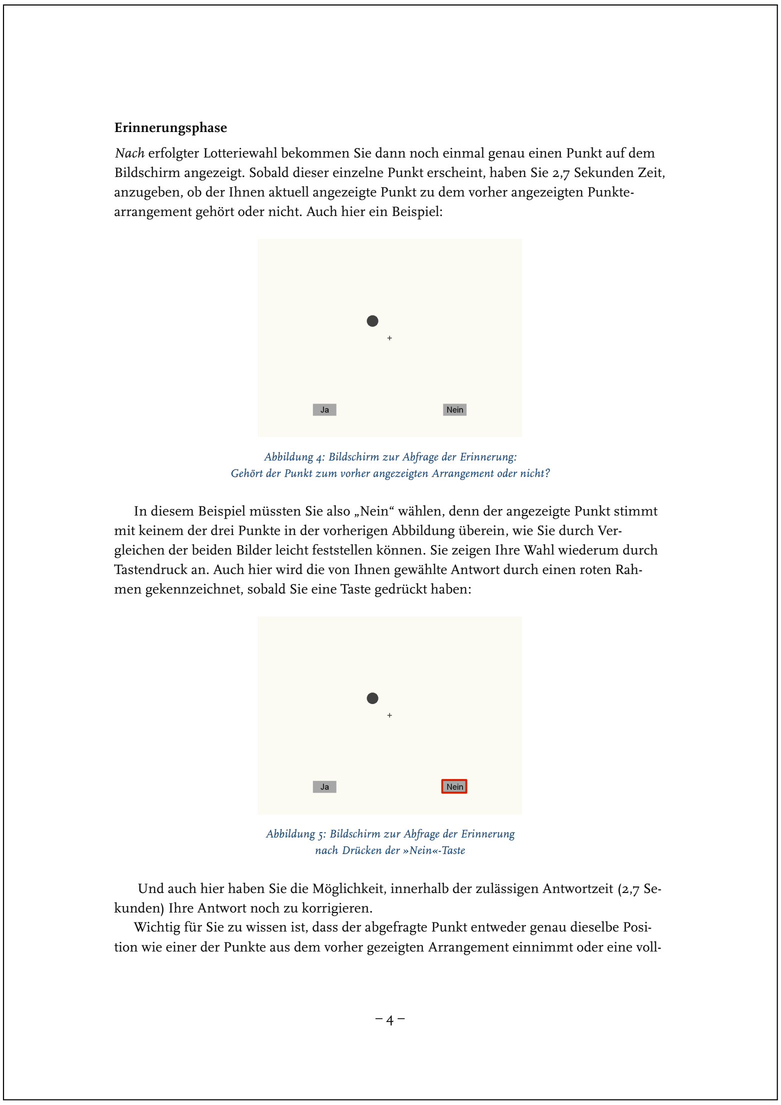
[Figure 3. Screen with the arrangement of dots to remember]

The arrangement of dots will be presented for exactly one second. Your task is to keep this arrangement in mind while making the lottery choice. (The display of the arrangement of dots is followed by a so-called "mask" that consists of 99 narrowly spaced dots. This mask is of no further relevance for you; its sole purpose is to prevent an afterimage of the arrangement of dots on your retina.)

During the memorizing phase, the fixation cross in the middle of the screen is shown in red. This is supposed to serve as a signal to you that you are currently in the memorizing phase.

Probe Phase

After the time frame for the lottery choice, you are shown exactly one dot on the screen. As soon as this single dot appears, you are granted 2.7 seconds to indicate whether the dot that is currently presented was part of the previously shown arrangement of dots or not. Again, an example:


Erinnerungsphase

Nach erfolgter Lotteriewahl bekommen Sie dann noch einmal genau einen Punkt auf dem Bildschirm angezeigt. Sobald dieser einzelne Punkt erscheint, haben Sie 2,7 Sekunden Zeit, anzugeben, ob der Ihnen aktuell angezeigte Punkt zu dem vorher angezeigten Punkte-arrangement gehört oder nicht. Auch hier ein Beispiel:

Abbildung 4: Bildschirm zur Abfrage der Erinnerung: Gehört der Punkt zum vorher angezeigten Arrangement oder nicht?

In diesem Beispiel müssten Sie also „Nein" wählen, denn der angezeigte Punkt stimmt mit keinem der drei Punkte in der vorherigen Abbildung überein, wie Sie durch Vergleichen der beiden Bilder leicht feststellen können. Sie zeigen Ihre Wahl wiederum durch Tastendruck an. Auch hier wird die von Ihnen gewählte Antwort durch einen roten Rahmen gekennzeichnet, sobald Sie eine Taste gedrückt haben:

Abbildung 5: Bildschirm zur Abfrage der Erinnerung nach Drücken der »Nein«-Taste

Und auch hier haben Sie die Möglichkeit, innerhalb der zulässigen Antwortzeit (2,7 Sekunden) Ihre Antwort noch zu korrigieren.

Wichtig für Sie zu wissen ist, dass der abgefragte Punkt entweder genau dieselbe Position wie einer der Punkte aus dem vorher gezeigten Arrangement einnimmt oder eine voll-

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[Figure 4: Decision screen for the probe phase: Does the dot belong to the previously shown arrangement or not?]

In this example you would have to choose "No," since the presented dot does not coincide with any of the three dots in the previous figure, as you can easily confirm by comparing the two images. You again indicate your choice by pressing a key. Also in this stage, the answer that you have given is highlighted by a red frame as soon as you have pressed the key:

[Figure 5: Decision screen for the probe phase after pressing the "No" key]

Here, again, you have the opportunity to correct your answer within the granted time frame (of 2.7 seconds).

It is important for you to know that the dot in the probe phase either occupies exactly the same location as the respective dot from the arrangement of dots in the memorizing phase or a completely non-overlapping location. That is, there is no ambiguity as to whether the probe belonged to the arrangement or not.

In contrast to the memorizing phase, the fixation cross is shown in black, instead of red, during the probe phase.

Number of Rounds

Payoff-Relevant Rounds

You will complete a total of 150 rounds (+ 30 practice rounds). All rounds are grouped into blocks of 15 rounds. In-between blocks, you have the possibility to take a break for as long as you like. There are three types of rounds:

- In 60 out of 120 rounds you will not have to do any other task besides the lottery choice.
- In another 60 rounds, you will be given the task to remember the arrangement of dots, as described above, in addition to the lottery choice.
- In the remaining 30 rounds, you will be given only the task to remember the arrangement of dots, without making any lottery choice.

Within a block, all rounds are of the same type: they either all include the memorization task or they don't, and they either all include the lottery choice or don't.

Practice Rounds

To provide you with the opportunity to get acquainted with the tasks, the experiment will start with 30 practice rounds; there will be 10 practice rounds for each of the three types described above.

These practice rounds differ from the "real" rounds in two aspects: (1) The practice rounds are *not* included in determining your payoffs. (2) During the practice rounds, you will receive feedback as to whether you answered correctly in the memorization task—while you will not receive any feedback in the "real" rounds. Moreover, during the practice rounds, you will be informed of the randomly determined payoff drawn from the lottery that you have selected (i.e., the monetary payoff that you would have received will be highlighted by a red marker on the screen). In contrast, for the "real" rounds you will be informed of your payoff only at the very end of the experiment—as described in the following section.

ständig nicht überlappende Position. Das heißt, es gibt keinerlei Unklarheit bei der Kategorisierung, ob der Punkt zu dem Arrangement gehörte oder nicht.

Anders als in der Einprägungsphase ist das Fixationskreuz in der Erinnerungsphase schwarz, und nicht rot, eingefärbt.

Anzahl der Durchgänge

Auszahlungsrelevante Durchgänge

Sie absolvieren insgesamt 150 Durchgänge (+ 30 Probedurchgänge). Die Durchgänge sind in kurze Blöcke von jeweils 15 Durchgängen gegliedert. Zwischen den Blöcken haben Sie stets die Möglichkeit, sich – so lange sie möchten – auszuruhen. Es gibt drei Typen von Durchgängen:

- In 60 von 120 Durchgängen werden Sie neben der Lotteriewahl *keine* weitere Aufgaben bearbeiten müssen.
- In 60 anderen Durchgängen werden Sie zusätzlich zu der Lotteriewahl die oben beschriebene Punkte-Erinnerungs-Aufgabe gestellt bekommen.
- In den übrigen 30 Durchgängen werden Sie nur die Punkte-Erinnerungsaufgabe ohne Lotteriewahl gestellt bekommen.

Alle Durchgänge innerhalb eines Blocks sind vom gleichen Typ: entweder sämtliche mit oder ohne Erinnerungsaufgabe bzw. sämtliche mit oder ohne Lotteriewahl.

Probedurchgänge

Um sich an die Aufgabe zu gewöhnen, absolvieren Sie zu Beginn des Experiments 30 Probedurchgänge; von jedem der drei oben genannten Typen gibt es 10 Probedurchgänge.

Die Probedurchgänge unterscheiden sich von den „richtigen" Durchgängen in zwei Punkten: (1.) Die Probedurchgänge gehen *nicht* in die Ermittlung Ihrer Auszahlung ein! (2.) Während der Probedurchgänge erhalten Sie Feedback, ob Sie die Erinnerungsaufgabe korrekt gelöst haben – in den „echten" Durchgängen gibt es kein Feedback. Außerdem bekommen Sie in den Probedurchgängen angezeigt, was das Ausspielen der von Ihnen gewählten Lotterie ergeben hat (der Betrag, den Sie ausgezahlt bekämen, wird auf dem Bildschirm dick rot unterstrichen). In den „echten" Durchgängen erfahren Sie dies hingegen erst ganz am Ende des Experiments – wie im folgenden Abschnitt beschrieben.

Auszahlungen

Für Ihre Teilnahme

Für Ihre Teilnahme erhalten Sie einen festen Betrag i. H. v. 5 €.

Für die Lotteriewahl

Von den insgesamt 150 auszahlungsrelevanten Durchgängen wird vom Computer völlig zufällig genau ein Durchgang ausgelost. Anschließend wird genau die Lotterie, die Sie in ebenjenem Durchgang gewählt haben, ausgespielt. Dies bedeutet, dass sie in jedem

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Payments

For Your Participation

For participating in this experiment you receive a fixed base payment of €5.

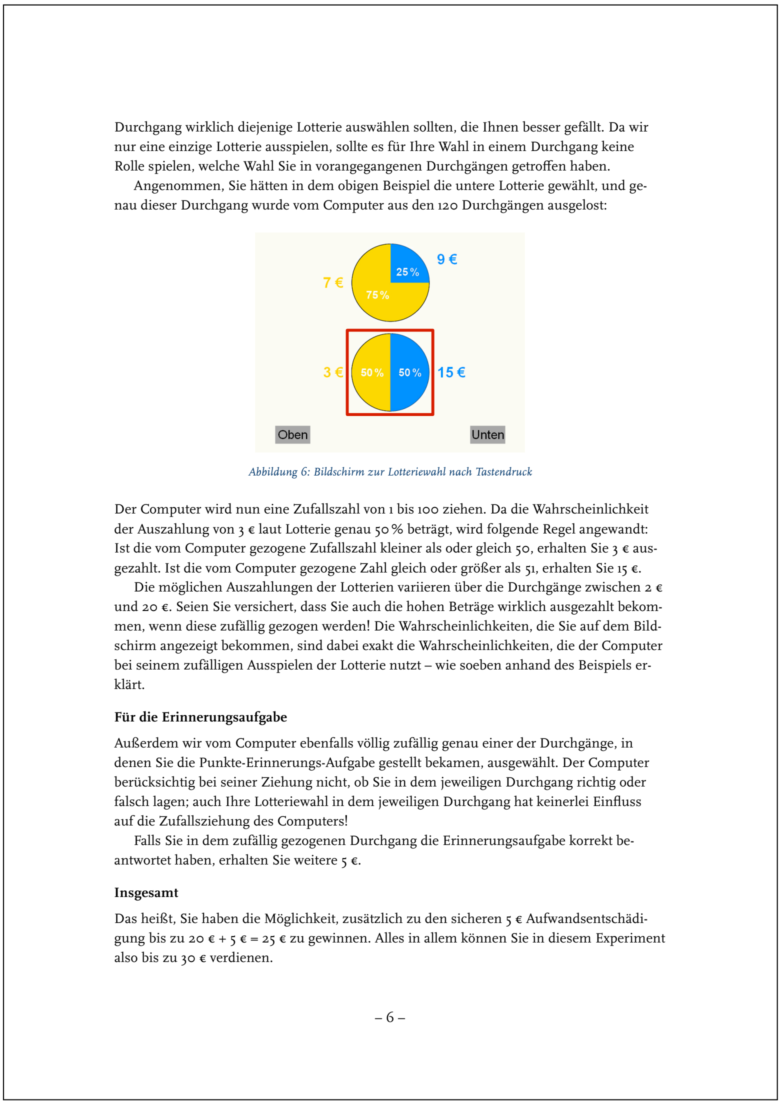
[Figure 6: Decision Screen for the Lottery Choice after Key Press]

For the Lottery Choice

Out of the 150 payoff-relevant rounds in total, the computer will select a single round randomly. Afterwards, exactly the lottery that you have chosen in that particular round will be used to determine your payoff. This implies that you should, in every single round, select the one lottery that you like better. Since we use a single lottery in order to determine your payoff, it ought to make no difference for your current choice how you have decided in previous rounds.

Let us assume that you had chosen the bottom lottery in the above example and that exactly this round was selected by the computer out of all 120 rounds:

The computer will now draw a random number from the range 1–100. Since the probability of the €3 payoff is exactly 50%, the following rule is applied: If the number randomly drawn by the computer is less than or equal to 50, you will be paid €3. If the number randomly drawn by the computer is greater than or equal to 51, you will receive €15.



Durchgang wirklich diejenige Lotterie auswählen sollten, die Ihnen besser gefällt. Da wir nur eine einzige Lotterie ausspielen, sollte es für Ihre Wahl in einem Durchgang keine Rolle spielen, welche Wahl Sie in vorangegangenen Durchgängen getroffen haben.

Angenommen, Sie hätten in dem obigen Beispiel die untere Lotterie gewählt, und genau dieser Durchgang wurde vom Computer aus den 120 Durchgängen ausgelost:

Abbildung 6: Bildschirm zur Lotteriewahl nach Tastendruck

Der Computer wird nun eine Zufallszahl von 1 bis 100 ziehen. Da die Wahrscheinlichkeit der Auszahlung von 3 € laut Lotterie genau 50 % beträgt, wird folgende Regel angewandt: Ist die vom Computer gezogene Zufallszahl kleiner als oder gleich 50, erhalten Sie 3 € ausgezahlt. Ist die vom Computer gezogene Zahl gleich oder größer als 51, erhalten Sie 15 €.

Die möglichen Auszahlungen der Lotterien variieren über die Durchgänge zwischen 2 € und 20 €. Seien Sie versichert, dass Sie auch die hohen Beträge wirklich ausgezahlt bekommen, wenn diese zufällig gezogen werden! Die Wahrscheinlichkeiten, die Sie auf dem Bildschirm angezeigt bekommen, sind dabei exakt die Wahrscheinlichkeiten, die der Computer bei seinem zufälligen Ausspielen der Lotterie nutzt – wie soeben anhand des Beispiels erklärt.

Für die Erinnerungsaufgabe

Außerdem wir vom Computer ebenfalls völlig zufällig genau einer der Durchgänge, in denen Sie die Punkte-Erinnerungs-Aufgabe gestellt bekamen, ausgewählt. Der Computer berücksichtig bei seiner Ziehung nicht, ob Sie in dem jeweiligen Durchgang richtig oder falsch lagen; auch Ihre Lotteriewahl in dem jeweiligen Durchgang hat keinerlei Einfluss auf die Zufallsziehung des Computers!

Falls Sie in dem zufällig gezogenen Durchgang die Erinnerungsaufgabe korrekt beantwortet haben, erhalten Sie weitere 5 €.

Insgesamt

Das heißt, Sie haben die Möglichkeit, zusätzlich zu den sicheren 5 € Aufwandsentschädigung bis zu 20 € + 5 € = 25 € zu gewinnen. Alles in allem können Sie in diesem Experiment also bis zu 30 € verdienen.

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The payoffs included in the lotteries range between-rounds from €2 to €20. We assure you that the high payoffs will indeed be paid in the case that they are selected! The probabilities displayed on the screen are the exact probabilities that the computer will use in determining the selected lottery's payoff—as it was just explained in the example.

For the Dots Memorization Task

Moreover, the computer will select, again completely randomly, exactly one of the rounds in which you faced the dots memorization task. In its selection, the computer does not take into account whether you have answered correctly or incorrectly in the respective round; moreover, your lottery choices have no influence whatsoever on the computer's random determination of the round that will count for the dots memorization task!

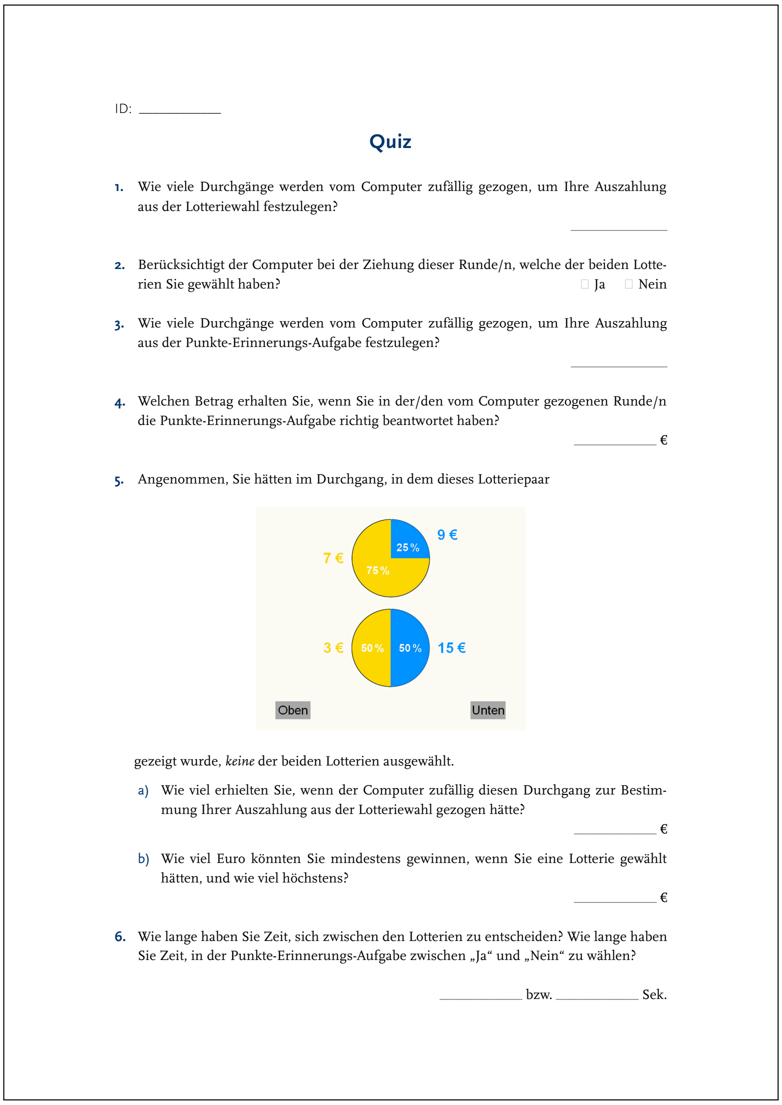
In the case that you answered correctly in the randomly drawn round for the memorization task, you will be paid an additional €5.

Total Payoff

This means that you have the opportunity to win up to an additional €20 + €5 = €25 on top of the fixed base payment. In other words, you can earn up to €30 in total during this experiment.

Quiz

1. How many rounds are randomly selected by the computer in order to determine your payoff from the lottery choice? __________
2. When selecting this round, does the computer take into account which of the two lotteries you have chosen? ☐ Yes ☐ No
3. How many rounds does the computer select randomly in order to determine your payoff from the dots memorization task? __________
4. What is the monetary amount that you will receive in the case that you have answered correctly in the computer-drawn round of the dots memorization task? €__________
5. Suppose that you did not select any lottery in the round in which the following lottery pair was displayed: [lottery at the top: (€7, 75%; €9, 25%); lottery at the bottom: (€3, 50%; €15, 50%)].
   a) How much money would you be paid if the computer randomly selected this very round as the one that counts for your payoff from the lottery choice? €__________
   b) How much money would you be paid at least if you had selected one of the two lotteries, and how much at most? €__________
6. How much time are you granted to decide between the lotteries in a given round? And how much time are you granted to choose between “Yes” and “No” in the dot memorization task? __________ sec. and __________ sec., respectively


ID: __________

Quiz

1. Wie viele Durchgänge werden vom Computer zufällig gezogen, um Ihre Auszahlung aus der Lotteriewahl festzulegen? __________
2. Berücksichtigt der Computer bei der Ziehung dieser Runde/n, welche der beiden Lotterien Sie gewählt haben? ☐ Ja ☐ Nein
3. Wie viele Durchgänge werden vom Computer zufällig gezogen, um Ihre Auszahlung aus der Punkte-Erinnerungs-Aufgabe festzulegen? __________
4. Welchen Betrag erhalten Sie, wenn Sie in der/den vom Computer gezogenen Runde/n die Punkte-Erinnerungs-Aufgabe richtig beantwortet haben? __________ €
5. Angenommen, Sie hätten im Durchgang, in dem dieses Lotteriepaar

gezeigt wurde, *keine* der beiden Lotterien ausgewählt.
   a) Wie viel erhielten Sie, wenn der Computer zufällig diesen Durchgang zur Bestimmung Ihrer Auszahlung aus der Lotteriewahl gezogen hätte? __________ €
   b) Wie viel Euro könnten Sie mindestens gewinnen, wenn Sie eine Lotterie gewählt hätten, und wie viel höchstens? __________ €
6. Wie lange haben Sie Zeit, sich zwischen den Lotterien zu entscheiden? Wie lange haben Sie Zeit, in der Punkte-Erinnerungs-Aufgabe zwischen „Ja“ und „Nein“ zu wählen? __________ bzw. __________ Sek.

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